Income Tax Noncompliance and Professional License Suspension: Evidence from a Natural Experiment in Missouri

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Abstract:
Laws in more than a dozen states require regulators to suspend the professional license of taxpayers who are noncompliant in their state income taxes. Given the potentially negative consequences that stem from the enforcement of these regulations (unemployment or underemployment), we argue that these policies will lead to either few license suspensions or license suspensions that are primarily concentrated among taxpayers who are financially constrained. We proxy for financial constraints using measures of income and contingent employment. Using novel data from the state of Missouri, we observe that for several lower-income professions nearly 10% of licenses are suspended over the course of our 8-year sample. We also find that license suspensions are common in professions where contingent employment arrangements are prevalent. Overall, this pattern of results suggests that license suspensions for income tax noncompliance are frequent and may be driven by financial constraints.

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Introduction

What predicts personal income tax noncompliance? Sizable literatures in economics and accounting shed light on this issue. For example, basic theoretical models predict that taxpayers weigh the benefits of successfully cheating against the likelihood of detection and punishment (Allingham and Sandmo 1972). Empirical research generally supports these theoretical predictions but also finds that tax noncompliance is associated with fairness concerns, income sources (employment vs. self-employment income), income levels, age, and gender (Slemrod 2007 and Alm 2012). Importantly, most of this research is premised on the idea that individuals avoid taxes at their discretion. That is, they face a choice of whether or not to comply. Accordingly, most related policy interventions are designed to influence this compliance decision faced by taxpayers.

In recent years, a large number of states have adopted policies that allow the suspension of professional and/or driver's licenses when individuals are noncompliant with their state tax obligations. These policies presume that taxpayers have the means to pay their taxes but choose not to. For example, New York Governor Andrew Cuomo declared that his state's law would put "tax scofflaws" on notice (New York State Tax Department 2013). While these policies create a potent penalty for taxpayers choosing not to comply, they may also have significant consequences for taxpayers where, at the time the tax is due, non-payment is not a choice. Specifically, there may be a group of taxpayers who are noncompliant because they are financially constrained and unable to cover even minimal tax expenses out of savings or through borrowing (Bricker et al. 2017 and Cornfield 2017). Surprisingly, despite the use of license suspension policies in California, Delaware, Illinois, Indiana, Iowa, Maine, Maryland, Massachusetts, Minnesota, Missouri, New Jersey, New York, Oklahoma, Oregon, Vermont, and

Wisconsin, no research to date examines the outcomes of these policies. In this paper, we provide evidence about the types of taxpayers who have their professional licenses suspended for tax noncompliance.

We argue that these policies will lead to either few license suspensions or license suspensions that are primarily concentrated among financially constrained taxpayers. If taxpayers are simply choosing not to pay taxes, we expect this policy to be an effective deterrent and lead to high tax compliance and a low incidence of license suspension. That is, given the costly and imminent penalty of not paying taxes, it is straightforward to expect that taxpayers would satisfy their outstanding tax debt. Further, if these outstanding state income tax liabilities were mostly explained by discretionary shirking, then it is likely that the few penalties that are applied would be largely unrelated to financial constraints.

However, if these outstanding state income tax liabilities are material for some taxpayers, and their income tax noncompliance is more reflective of financial constraints as opposed to shirking, then we would likely see the suspension of a considerable portion of professional licenses and in a predictable pattern. Specifically, we predict that there will be more suspensions among lower-income taxpayers and taxpayers engaged in contingent employment situations. We predict professional license suspensions will be prevalent among lower-income earners because of the liquidity and borrowing constraints faced by the bottom quintile of wage-earners (Cornfield 2017; Bricker et al. 2017). We predict higher professional license suspensions among taxpayers in contingent employment situations because workers in these arrangements are regularly employed via third party staffing or contracting firms, and often work under 1099 arrangements. Income tax withholding may be imperfect in these settings, as employees may move between staffing firms, which could leave taxpayers facing a high tax liability at the year's end (Kalleberg 2000). This high tax liability would be hard for financially constrained taxpayers to cover and, therefore, could result in a larger number of license suspensions.

We explore these predictions using a natural experiment provided by a policy in Missouri. In 2003, the Missouri state government imposed a law that required professional licensing boards in the state, under the jurisdiction of the Missouri Division of Professional Registration (DPR), to report the names and social security numbers of new and renewing license-holders to the state Department of Revenue (DOR). The law empowered the Missouri DOR to suspend the professional license of any Missouri taxpayer who was delinquent in their taxes or had not filed state income taxes in the prior three years. The Missouri DPR regulates nearly all professional licensing boards in the state, which means the law applies to a wide cross section of professions, including cosmetologists, massage therapists, tattoo artists, licensed practical nurses, accountants, pharmacists, architects, surveyors, boxers, realtors, professional wrestlers, and doctors.

While many states have adopted laws that suspend professional licenses for tax delinquency, we focus our empirical analyses on Missouri for reasons of data availability. We are able to obtain Missouri suspension data due to a quirk in the Missouri DPR's reporting of these suspensions to federal regulators. In an effort to prevent potentially dangerous medical practitioners from evading notice by crossing state lines, in 1986 the US Congress charged the Department of Health and Human Services with tracking state level licensure suspensions, medical board sanctions, and malpractice payouts. This data is currently housed in the National Practitioners Data Bank (NPDB), maintained by the Bureau of Health Workforce, and is available in an anonymized file to researchers. Most of the violations in the NPDB are for issues like medical malpractice and unprofessionalism. Missouri is unique among states for reporting to

NPDB professional license suspensions relating to income tax noncompliance. This unfortunately results in small samples for our empirical analyses, but if the application of the Missouri law is otherwise analogous to the experience of other states with similar legislation, then the patterns of income tax noncompliance we identify in Missouri likely extends to other states as well.

The NPDB public research file, which contains the Missouri DPR's tax related professional license suspensions, is anonymized. That is, we have no personally identifying information on the individuals who are noncompliant in their taxes in the face of a professional license suspension. This is a considerable constraint of the data. The only variables provided in the public NPDB data is the date, type of suspension (e.g., tax related, malpractice related, crime related), and type of license being suspended (doctor, nurse, physical therapist, massage therapist, etc.). Accordingly, we are only able to analyze this data at a profession level. That is, we are only able to identify the income, benefits provisions, etc. of a taxpayer who has their professional license suspended using profession-level medians.

We observe, in both the descriptive statistics and multivariate regressions, that professional licenses suspensions for tax noncompliance are not uncommon among lower-income professions. For example, the descriptive statistics reveal that for several low income occupations about 10% of professional licenses are suspended for income tax noncompliance over the course of our 8-year sample. Further, our regression analysis indicates that for the otherwise median occupation, shifting wages from the ninth to first wage decile ($113,000 to $20,000) more that triples the expected frequency of license suspensions. We also find evidence that professional license suspensions are particularly prevalent in contingent or casual employment situations, after controlling for wages. These results suggest that license suspensions for income tax noncompliance are frequent and may be driven by financial constraints.

To put these results into context, we note that Missouri has a relatively flat state income tax structure, and the total state income tax liability for taxpayers in lower-income professions is typically only a few hundred dollars (e.g., $200 to $600). This amount seems trivial, but should be considered against survey evidence that suggests a significant minority of low-income earners are both credit constrained (Bricker et al. 2017) and unable to cover a $500 expense out of savings (Cornfield 2017).[1] Discussions with Missouri DOR revenue agents confirm this conjecture. DOR agents indicate that in their correspondence with these noncompliant taxpayers, the typical message they receive is one of liquidity constraints leading to very modest tax liabilities (on the order of a few hundred dollars) being unpayable.

Our research makes at least two contributions. First, we document that Missourians who are more likely to be financially constrained have a high rate of professional license suspension for tax delinquency. We are the first to document any kind of outcome related to this policy. Due to the increasingly pervasive nature of these types of policies our finding is an important first step. For example, beyond taxes, 19 states can seize state-issued professional licenses from residents who default on student loan debt (Silver-Greenberg et al. 2017). Given the widespread use of professional and driver license suspension programs, understanding which portion of the population they are impacting is potentially useful.

Second, we add to a substantial literature that examines personal income tax noncompliance. While this literature examines numerous factors, financial constraints are not a

[1] This survey evidence is supported by a sizable economics literature examining individuals' credit and liquidity constraints (e.g., Gross and Souleles 2002; Jappelli 1990; Adams et al. 2009; Hayashi 1985; Johnson et al. 2006; Morse 2011; Hall and Mishkin 1982; Brown and Karl 2008).

widely discussed motivation of income tax noncompliance. For example, in two of the best recent discussions of the tax evasion literature, Slemrod (2007) and Alm (2012) mention as motivators of evasion: fairness concerns, income sources, income levels, age, gender, potential penalties, and the likelihood of detection. Similarly, their summations of recent policy interventions targeting tax evaders center on deterrence via enforcement and behavioral appeals. None of these predictors, or the resulting policy efforts, reflect the fact that the economics of tax compliance may be, at least at the time of the tax bill coming due, virtually impossible for some individuals to navigate. The literature using analytical models to explain individual income tax compliance (starting with Becker 1968 and Allingham and Sandmo 1972) is also thorough, but is similarly premised on the notion that noncompliance is a discretionary choice (for a review of this literature, see Sandmo 2005).

However, several prior studies allude to the pressures we describe. Most related is Ritsema et al. (2003), that documents the response to an Arkansas state income tax amnesty program. The program forgave all interest and penalties to delinquent Arkansas taxpayers who applied during a given window. The mean income of taxpayers taking advantage of the program who admitted to intentional noncompliance was about $36,000, and the median outstanding tax liability was about $500. When asked about their excuse for noncompliance, one of the most common responses was “lack of money.” We take this as suggestive of financial constraints driving some portion of income tax noncompliance, and we document further evidence of this understudied but important constraint.

Further, Erard and Ho (2001) try to estimate the prevalence of “ghosts”, or income earners who do not file tax returns at all. Our discussions with the Missouri DOR suggest that many of the delinquent taxpayers in our sample could be defined similarly as ghosts. The

Missouri DOR tries to identify tax evaders using an income tax gap model similar to those applied in empirical tax evasion studies (e.g., Feinstein 1991; Blumenthal et al. 2001; Slemrod et al. 2001; Hurst et al. 2013; Gorodnichenko et al. 2009), but the easiest cases of evasion to identify for the DOR are those where there is no tax filing but there is a record of the individual in question maintaining a professional license in the state. We are unable to determine which of our suspensions result from ghosts versus filers who did not satisfy the entirety of their tax burden, but conversations with Missouri revenue agents suggest that the former category represents at least a sizable minority of cases.

While we believe our paper makes a meaningful contribution, there are questions we are not able to answer. For example, we are unable to test how much shirking behavior is curtailed by the threat of license suspension in Missouri. That is, we do not know how many taxpayers received demand letters from the Missouri DOR and rectify their delinquency prior to a license suspension. This would be interesting data to analyze, and we submitted an open records request to the Missouri DOR in an effort to collect it, only to be told that the DOR does not track demand letters on a per profession basis. Requesting this information from another state may be a fruitful avenue for future exploration.[2]

We are also unable to quantify the costs of losing a license. Because the State of Missouri only suspends licenses at the time of initial application or renewal, it seems likely that individuals losing their license will end up un- or under-employed, or at least bear the switching costs involved with involuntary job loss. That is, the license in question is clearly valuable to these noncompliant taxpayers, as they were very recently willing to expend time and money to

[2] Data privacy concerns preclude the DOR from sharing the actual letters, which would include the type of professional license.

apply for or renew said license.[3] The broad literature on job loss highlights many costs and suggests that these Missourians with suspended licenses could see lower future wages, experience higher rates of addiction, homelessness, and crime, and negatively affect their children's educational attainment and partners' mental health (e.g., Norcross and Hamilton 2010; Helliwell and Huang 2014; Feldstein 1978; Young 2012; von Wachter and Handwerker 2009; Farber et al. 1993; Eliason and Storrie 2009; Stevens and Schaller 2011; Coelli 2011; von Wachter et al. 2009; Mendolia 2014; Rege et al. 2011; Catalano et al. 1993; Catalano et al. 1997; Shinn et al. 2007). Future research that documents some of these costs would be valuable.

In the following sections we outline our data and statistical tests, report empirical results, and provide a concluding discussion.

Data and Empirical Methods

As mentioned in the previous section, the boards overseeing medical professionals in Missouri report tax related license suspensions to the Bureau of Health Workforce. We limit our study to the 16 largest healthcare professions included in the reported data. We make this design choice largely as a function of the availability of control variables (discussed below). We restrict our analysis to the years 2009-2016. The Missouri law in question, Section 324.010, RSMo, went into effect in 2003, but Missouri only began reporting tax related suspensions to federal regulators in 2009.

[3] Under reasonable assumptions, it is likely that even the lowest paid medical professionals will lose wages as a result of having their license suspended. For example, Table 2 shows that massage therapists work about 30 hours a week and earn $15,000 a year. If they work 50 weeks a year they would earn $10 an hour ($15,000/(30*50)). While we are not able to ascertain the jobs taken by taxpayers who lose their professional license, it seems unlikely they would move to a higher paid job (given that they just recently applied or reapplied for their license, presumably because it was the best option they had). If they move to a minimum wage job they would earn on average about $7.50 during our sample period, a 25% reduction in hourly wages for even the lowest paid medical professionals.

Our empirical approach revolves around predicting the number of professional license suspensions for income tax noncompliance as a function of profession-level characteristics. Every month, Missouri's DPR provides the names and social security numbers of new and renewing license holders to the Missouri DOR, and the Missouri DOR sends warning letters via certified USPS mail to all of the licensees who are delinquent in their income taxes for the prior three years.[4] Multiple warning letters will be sent to a licensee requesting they pay their taxes. For a licensee who fails to remediate an outstanding tax debt, the Missouri DOR notifies the Missouri DPR to suspend the license in question. By law, this suspension requires that professionals immediately cease all activity falling under the purview of the suspended license (e.g., nurses with suspended licenses can no longer work as nurses). Upon satisfying this debt, the Missouri DOR then provides the taxpayer in question with a certification of compliance. To end the suspension of their professional license, the taxpayer need only present this certification to their appropriate licensing board.

We report the counts of these professional license suspensions for state income tax noncompliance by year and profession in Table 1. Also included in Table 1 is the number of professionals working in each field in the state of Missouri by year, as estimated by the Bureau of Labor Statistics. This allows us to compute the percentage of state income tax noncompliance for each profession by dividing the number of tax related suspensions by the number of total workers.

We also report sum totals of the count and percentage of license suspensions per profession over the course of our sample period in Table 1. This univariate evidence does not support the premise that the Missouri law in question operates only to deter state income tax

[4] Data provided to us by the Missouri DOR shows nearly 3,750 warning letters were sent in 2017.

noncompliance that is characterized as discretionary shirking behavior. Rather, a surprisingly high proportion of licenses are suspended among lower income professions. For example, 13.9% of massage therapists see a license suspension for income tax noncompliance over the course of our 8-year sample. Similarly, about 9.5% of licensed practical nurses (LPNs) see their professional license suspended for state income tax delinquency. By comparison, doctors, dentists, nurses, and pharmacists see suspension rates in the 0.1% to 2% range over our 8-year period.

These univariate comparisons are stark, but in continuing analysis we turn to regression models. In doing so we include other control variables that could influence the enforcement of the Missouri law, as well as known covariates of income tax evasion. We draw these control variables from the U.S. Census Public Use Microdata Sample (PUMS). The PUMS data contains individual census-taker responses for a random cross-section of 1% of U.S. respondents per year (Schroeder 2017). We use the 5-year combined 2010-2014 PUMS sample to collect covariates, and we restrict our analysis to professions with at least 10 Missouri respondents appearing in this PUMS data.

Table 2 reports summary statistics for these variables of interest for the 16 professions that meet this data requirement, as well as summary data on profession size and professional license suspensions related to income tax noncompliance. Also included are variables relating to education, wealth, immigration status, English proficiency, unemployment, wages, and benefits. Many of these variables are not included in our multivariate analysis, but are instead provided in Table 2 to engender better understanding of the underlying data.

Table 1 identifies Massage Therapists and LPNs as having (by far) the highest rates of income tax noncompliance (as proxied by professional license suspension rates). Table 2 suggests that these rates may be related to financial constraints, as these two professions see low median wages ($15,000 and $28,000, respectively) and high rates of enrollment in welfare programs (percent of profession receiving public assistance or Medicaid) of 4% and 7%, respectively.

In regression models further exploring income tax noncompliance, other controls are needed to proxy for factors affecting the enforcement of the Missouri program and broader predictors of income tax compliance. First, we include a covariate called *% Self-employed*, as self-employment income is easier to hide from tax authorities and is subsequently reported at lower rates (Feinstein 1991; Blumenthal et al. 2001; Slemrod et al. 2001). We define *% Self-employed* as the proportion of professionals in the PUMS census data who report that self-employment wages make up half or more of their total wage earnings. We also include *% Moved Recently*, as the Missouri program is enforced via certified letter, and these letters may reach the intended recipient at lower rates in more itinerant populations (or, conversely, it may be more difficult for the Missouri DOR to locate and enforce the rule on delinquent taxpayers who move frequently). We define *% Moved-recently* as the proportion of professionals who have reported moving in the prior 12 months (reported in the PUMS census data). Finally, as we use count models to predict the frequency of income tax noncompliance driven professional license suspensions, we include a control for the overall size of the profession. This variable, *Ln(Workers in Profession)*, is constructed from profession and state level count data released annually by the Bureau of Labor Statistics.

We use these controls and other variables of interest (namely related to financial constraints) to estimate negative binomial count models that predict the frequency of license suspensions for income tax noncompliance by profession and year. We cluster standard errors by profession.

Results

We report the first set of these models in Table 3. Model 1 reports a baseline specification that includes profession size, rate of self-employment, and itinerancy (% who moved in last 12 months). The coefficients on these control variables are significant in the expected direction. Models 2-5 each incorporate a separate measure of income, which is our first measure of financial constraints (*Ln(Median Wages)*, *Median Wages*, *Median Income-to-poverty Ratio*, *% on Welfare*). All of these covariates of interest load in a direction suggestive of financial constraints being a significant predictor of income tax noncompliance. In model 2 for example, with other covariates set at median levels, shifting wages from the ninth to first decile breakpoint ($113,000 to $20,000) more than triples the expected frequency of license suspensions. This suggests that the liquidity constraints common among low-income earners (e.g., Cornfield 2017) can make it difficult to satisfy nominally modest tax bills.

In Table 4, further tests are conducted to examine whether some explanation within the cross-section of taxpayers explains the pattern of result we observe. In particular, we are interested in whether the professions that see high levels of income tax noncompliance also see fewer opportunities for work. This does not appear to be the case. Models 1 and 2 add to the baseline specification (controlling for profession size, % self-employed, % moved recently, and the natural log of median wages) measures of the number of weeks worked per year. Contrary to the notion that lower-income professionals may just not be getting enough work, it appears that the % of weeks worked is a marginally significant positive predictor of the frequency of income tax non-compliance, which is line with individuals employed in lower-income professions not taking much vacation time or sick leave. Model 3 also observes no relation between hours worked in a typical week and income tax noncompliance. Broadly, these three specifications suggest that lower-income earners do not skip out on tax liabilities due to not working enough.

Models 4 and 5 of Table 4 examine whether income tax noncompliance is predicted by formal employment arrangements, our second measure of financial constraints. Several factors could contribute to a lack of such arrangements increasing the prevalence of income tax noncompliance (White et al. 1993). First, workers in these arrangements are regularly employed via third party staffing or contracting firms, and often work under 1099 arrangements. Income tax withholding may be imperfect in these settings, as employees may move between staffing firms, which could leave unsophisticated taxpayers facing an unexpectedly high tax liability at the year's end (Kalleberg 2000). Second, a lack of employer provided benefits could also indirectly lead to liquidity constraints stemming from unexpected costs arising from healthcare treatments, for example (Babiarz et al. 2013; Finkelstein et al. 2012; Gross and Notowidigdo 2011). Third, even without unexpected healthcare costs, a lack of employer provided benefits (like health insurance) leads to workers having less disposable income (for things like tax liabilities), as they typically seek to purchase insurance or retirement products in private markets (and these costs are nontrivial, see Dickstein et al. 2015; Ericson and Starc 2015).

We proxy for casual/contingent/informal employment arrangements via the provision of employer provided health insurance. In addition to the baseline controls in Table 4 (workforce size, self-employment rate, itineracy, and income), models 4 and 5 incorporate the proportion of employees receiving health insurance from their employer (including and excluding the self-employed, respectively). In both models, we observe that income tax noncompliance increases in the proportion of workers in a profession in contingent working arrangements. This effect is larger than that obtaining from wage levels. Specifically, with all of the other covariates set at median levels in model 5, shifting the proportion of a professional workforce covered by an employer sponsored health insurance plan from the ninth decile (96%) to first decile (54%) increases the expected number of income tax noncompliance cases by a factor of 7 (an increase in the predicted annual rate of income tax noncompliance from about 0.08% to 0.55%). Given the penalties that accompany this noncompliance in our setting (i.e., the suspension of a professional license), it is likely that this noncompliance is due to financial constraints as opposed to shirking.

Robustness Checks

We are somewhat concerned that the enforcement of the Missouri tax compliance regime we study may wax and wane with the resources available to regulators (e.g., Jackson and Roe 2009). Likewise, it may be the case that regulators are constrained, and that suspensions in one profession negatively predict suspensions in another (i.e., by consuming the attention of regulators, see Kedia and Rajgopal 2011). We control for these effects in Table 5, where we include a variable named *Ln(1+Suspensions in Other Professions)* that adjusts for the number of tax related professional license suspensions that take place in professions in our sample for the year but outside of the focal profession. For medical doctors in 2010, for example, we would include the natural log of one plus the number of professional license suspensions levied against the other 15 professions in our sample in 2010 (i.e., we would subtract the 11 tax related suspensions for doctors from the total of 920 such suspensions in our entire sample in 2010).

Table 5 re-estimates our primary regressions including this new control variable. We observe results consistent with prior tests.

As a second robustness check, we also replicate our primary analyses excluding LPNs and massage therapists. These two professions have the highest rates of professional license suspensions for reasons of income tax noncompliance, and we are interested to see if our results rely on the inclusion of these outliers. In Table 6, we observe that wage-related covariates lose some statistical power in these tests, though all of these predictors remain directionally consistent. Furthermore, the proxies for contingent employment remain both economically and statistically significant.

Discussion

In recent years, a number of states have instituted laws mandating the suspension of state regulated professional licenses for workers who are noncompliant in their state income taxes.[5] We find that for medical professionals in the state of Missouri, license suspensions fall predominantly on low-income earners. For some of these workers (LPNs and massage therapists), nearly 10% of total licenses are suspended over the course of our 8-year sample.

It is unlikely that so many of these workers make a choice to give up their professional license to avoid a tax bill that is relatively paltry (on the order of a few hundred dollars), as they were very recently willing to expend the time and money necessary to apply for or renew said professional license. Rather, given the well-understood liquidity and credit constraints faced by

[5] Similar to Missouri, the license suspension laws in Illinois, Indiana, Maine, Maryland, Massachusetts, New Jersey, Oklahoma, Oregon, Vermont, and Wisconsin do not appear to require a minimum amount of tax due before a taxpayer's professional license can be suspended. In contrast, California only suspends the licenses of the top 500 taxpayers with delinquencies over $100,000, while Delaware requires the delinquent tax to be at least $2,500 and to arise from the occupation that the license relates to. Finally, Iowa and Minnesota require the outstanding taxes be $1,000 and $500, respectively, before they initiate license suspension proceedings.

much of this demographic, a more realistic explanation stems from their inability to satisfy even these nominally modest tax bills (Bricker et al. 2017; Cornfield 2017). This explanation is supported by anecdotal accounts in the public press that describe these types of suspensions and highlight the resulting financial hardships among those affected (Dewan 2015; Silver-Greenberg et al. 2017).

We also find that professional license suspensions are particularly prevalent in contingent or casual employment situations. This further supports our argument that financial constraints may be an important factor in state tax noncompliance as workers in these arrangements are regularly employed via third party staffing or contracting firms, and often work under 1099 arrangements. Income tax withholding may be imperfect in these settings, as employees may move between staffing firms, which could leave taxpayers facing a high tax liability at the year's end (Kalleberg 2000). This high tax liability would be hard for financially constrained taxpayers to cover and, therefore, could result in a larger number of license suspensions, consistent with our findings. From a policy perspective, this finding is potentially valuable. More and more workers are moving into casual and contingent work arrangements where income tax withholding is likely imperfect (De Stefano 2015; Burtch et al. 2018; Lobel 2017). By current estimates, about 16% of the U.S. labor force is in a contingent labor arrangement, up from about 11% a decade ago (Katz and Krueger 2019). Our results suggest that income tax noncompliance may be a considerable problem with this rapidly growing population.

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Table 1

Table 1 reports summary statistics on the number of license suspensions for income tax noncompliance by year and profession. Also included is the count of total workers per field by profession and the annual tax noncompliance rate (# of suspensions / # of workers).

Format: # of Lic. Suspen. for Tax Noncompl. # of Workers in Field Annual Tax Noncompliance Rate (%)	2009	2010	2011	2012	2013	2014	2015	2016	Sum Totals
Chiropractor	0	0	0	0	0	0	10	0	10
	510	510	510	500	580	550	560	590	
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.79%	0.00%	1.79%
Dental Asst.	0	0	0	0	9	3	0	0	12
	5,250	5,110	4,960	4,970	5,130	5,040	5,250	5,500	
	0.00%	0.00%	0.00%	0.00%	0.18%	0.06%	0.00%	0.00%	0.23%
Dental Hygienist	2	0	6	0	3	0	3	0	14
	2,240	2,560	2,830	2,940	2,820	3,130	3,140	3,110	
	0.09%	0.00%	0.21%	0.00%	0.11%	0.00%	0.10%	0.00%	0.50%
Dentist	7	0	6	0	10	0	11	0	34
	1,530	1,410	1,530	1,500	1,740	1,720	1,860	1,680	
	0.46%	0.00%	0.39%	0.00%	0.57%	0.00%	0.59%	0.00%	2.02%
Doctor	10	11	7	12	9	5	5	15	74
	10,330	11,360	11,690	12,160	12,460	11,730	11,480	10,120	
	0.10%	0.10%	0.06%	0.10%	0.07%	0.04%	0.04%	0.15%	0.66%
LPN or Vocational Nurse	309	591	21	343	10	368	11	11	1,664
	18,880	18,170	17,810	17,100	16,190	15,910	15,920	15,810	
	1.64%	3.25%	0.12%	2.01%	0.06%	2.31%	0.07%	0.07%	9.53%
Massage Therapist	30	4	25	4	33	2	27	4	129
	780	740	740	800	1,290	1,220	1,090	920	
	3.85%	0.54%	3.38%	0.50%	2.56%	0.16%	2.48%	0.43%	13.90%
Optometrist	2	0	3	0	1	0	0	0	6
	630	640	720	800	860	720	780	800	
	0.32%	0.00%	0.42%	0.00%	0.12%	0.00%	0.00%	0.00%	0.85%
Pharmacist	0	0	0	0	0	0	5	0	5
	5,510	5,700	5,520	6,030	5,680	6,010	6,310	6,570	
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.08%	0.00%	0.08%
Pharmacy Technician	0	1	1	0	0	134	136	16	288
	9,980	9,440	9,210	9,870	10,030	9,500	10,380	10,240	
	0.00%	0.01%	0.01%	0.00%	0.00%	1.41%	1.31%	0.16%	2.90%
Physical Therapy Asst.	0	0	0	9	0	4	1	4	18
	1,480	1,770	2,090	2,110	1,850	1,940	2,030	1,920	
	0.00%	0.00%	0.00%	0.43%	0.00%	0.21%	0.05%	0.21%	0.89%
Physical Therapist	0	0	0	4	0	2	0	1	7
	4,030	4,140	4,160	4,210	4,050	3,880	3,950	4,010	
	0.00%	0.00%	0.00%	0.10%	0.00%	0.05%	0.00%	0.02%	0.17%
Physician Asst.	0	0	1	0	0	0	0	1	2
	750	720	890	980	1,260	1,220	1,130	1,010	
	0.00%	0.00%	0.11%	0.00%	0.00%	0.00%	0.00%	0.10%	0.21%
Psychologist	0	5	0	3	0	0	0	0	8
	1,440	1,650	1,700	1,660	1,380	1,440	1,530	1,730	
	0.00%	0.30%	0.00%	0.18%	0.00%	0.00%	0.00%	0.00%	0.48%
Registered Nurse	12	308	272	16	264	12	337	8	1,229
	62,130	66,810	67,630	65,260	64,870	67,250	65,860	67,920	
	0.02%	0.46%	0.40%	0.02%	0.41%	0.02%	0.51%	0.01%	1.86%
Speech/Language Pathologist	0	0	1	0	4	0	1	0	6
	2,860	2,710	2,840	2,870	3,360	3,600	3,330	2,930	
	0.00%	0.00%	0.04%	0.00%	0.12%	0.00%	0.03%	0.00%	0.18%

Table 2

Table 2 reports summary statistics by profession. We have eight years of data (2009-2016) for 16 different professions, listed across the horizontal axis. Data on salaries and the number of workers per field is collected from the Bureau of Labor Statistics. Demographic data is collected from the US Census Public Use Microdata Sample (PUMS) for 2010-2014. Data on fraud frequencies per year is collected from the National Practitioner Data Bank (NPDB). The Missouri Department of Revenue and the Missouri Division of Professional licensing work together to suspend the licenses of delinquent taxpayers, and these suspensions are reported to the NPDB in an effort to track potentially dangerous medical workers (as mandated by Congress).

	Chiropractor	Dental Asst.	Dental Hygienist	Dentist	Doctor	LPN or Vocational Nurse	Massage Therapist	Optometrist	Pharmacist	Pharmacy Technician	Physical Therapy Asst.	Physical Therapist	Physician Asst.	Psychologist	Registered Nurse	Speech/Language Pathologist
Years worth of data	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
# of License Suspensions for Tax Noncompliance	10	12	14	34	74	1,664	129	6	5	288	18	7	2	8	1,229	6
# of Workers in Field (Max.)	590	5,500	3,140	1,860	12,460	18,880	1,290	860	6,570	10,380	2,110	4,210	1,260	1,730	67,920	3,600
Max Year Tax Noncompliance Rate	1.79%	0.18%	0.21%	0.59%	0.15%	3.25%	3.85%	0.42%	0.08%	1.41%	0.43%	0.10%	0.11%	0.30%	0.51%	0.12%
Mean Year Tax Noncompliance Rate	0.22%	0.03%	0.06%	0.25%	0.08%	1.19%	1.74%	0.11%	0.01%	0.36%	0.11%	0.02%	0.03%	0.06%	0.23%	0.02%
% of workers with poor English skills	0.00%	0.00%	0.00%	0.00%	1.13%	0.00%	0.00%	0.00%	1.02%	0.77%	0.00%	0.00%	3.57%	2.00%	0.46%	0.00%
% of workers who are immigrants	4.00%	4.27%	0.00%	2.82%	20.56%	2.29%	3.92%	0.00%	7.14%	5.79%	0.00%	8.82%	7.14%	2.00%	2.62%	0.00%
Modal Education in Profession (Cert. Type)	Prof. Deg.	Some Col.	Assoc.	Prof. Deg.	Prof. Deg.	Some Col.	Some Col.	Prof. Deg.	Prof. Deg.	HS Diploma	Assoc.	Bach.	Master's	Doctorate	Bach.	Master's
% of workers with employer provided health ins.	36.00%	66.67%	63.16%	39.44%	83.38%	66.82%	37.25%	83.33%	80.61%	72.97%	66.67%	80.88%	75.00%	68.00%	84.54%	88.89%
% of workers recieveing welfare	4.00%	4.27%	0.00%	0.00%	0.56%	7.32%	3.92%	0.00%	1.02%	4.25%	3.33%	0.00%	3.57%	2.00%	1.38%	0.00%
Median Income-to-Poverty Level ratio	4.40	3.31	≥ 5.01	≥ 5.01	≥ 5.01	3.08	2.83	≥ 5.01	≥ 5.01	2.79	2.88	4.31	4.99	≥ 5.01	4.76	≥ 5.01
% of workers who receive investment income	28.00%	5.13%	14.04%	33.80%	38.31%	4.35%	11.76%	33.33%	34.69%	5.02%	20.00%	17.65%	7.14%	28.00%	12.62%	12.70%
% of workers who are self-employed	36.00%	0.00%	1.75%	25.35%	6.76%	0.46%	31.37%	8.33%	1.02%	0.00%	0.00%	10.29%	0.00%	30.00%	1.08%	7.94%
% of workers who moved in the last year	12.00%	19.66%	8.77%	11.27%	10.99%	11.21%	19.61%	16.67%	10.20%	16.60%	30.00%	14.71%	7.14%	8.00%	10.31%	9.52%
# of workers surveyed in PUMS	25	117	57	71	355	437	51	12	98	259	30	68	28	50	1300	63
Median Wages	$ 27,200	$ 20,000	$ 40,000	$ 113,000	$ 145,000	$ 28,000	$ 15,000	$ 82,500	$ 100,000	$ 20,000	$ 21,150	$ 49,900	$ 38,400	$ 58,000	$ 45,000	$ 46,000
% who worked ≥ 40 weeks in the past year	88.00%	70.94%	85.96%	90.14%	93.24%	77.35%	82.35%	91.67%	78.57%	75.29%	73.33%	94.12%	92.86%	86.00%	84.08%	82.54%
% who worked ≥ 48 weeks in the past year	64.00%	64.10%	77.19%	80.28%	89.30%	73.46%	78.43%	91.67%	75.51%	70.66%	70.00%	82.35%	89.29%	80.00%	80.85%	73.02%
Median hours worked per week	36.5	35	32	36	50	40	30	40	40	40	40	40	40	40	40	40

Table 3

Table 3 reports negative binomial count models that predict the number of income tax noncompliance related professional license suspensions in the state of Missouri, by profession (n=16) and year (2009-2016). Standard errors are clustered at the profession level (n=16). *, **, and *** indicate two-tailed statistical significance at the p<0.1, p<0.05, and p<0.01 levels, respectively.

Count Models: DV = # of Tax Noncompliance Cases per Year per Profession					
Profession Level Independent Variables	Model 1	Model 3	Model 2	Model 4	Model 5
Ln(Workers in Profession)	1.872***	1.704***	1.787***	1.374***	1.471***
	[6.452]	[7.009]	[6.874]	[8.974]	[9.846]
% Self-Employed	8.518***	7.710***	8.565***	6.416***	7.393***
	[3.535]	[3.448]	[3.608]	[3.529]	[3.300]
% Moved Recently	10.300*	3.375	6.275	-5.508	5.393
	[1.903]	[0.832]	[1.384]	[-1.474]	[1.309]
Ln(Median Wages)		-0.938***			
		[-2.804]			
Median Wages (in thousands)			-0.014***		
			[-2.746]		
Median Income-to-poverty Ratio				-0.012***	
				[-4.344]	
% on Welfare					32.690***
					[4.189]
Constant	-15.634***	-3.389	-13.775***	-4.606**	-12.579***
	[-6.471]	[-0.996]	[-6.607]	[-2.521]	[-7.486]
Observations	128	128	128	128	128
Pseudo R^2	0.0854	0.097	0.0938	0.112	0.108

Table 4

Table 4 reports negative binomial count models that predict the number of income tax noncompliance related professional license suspensions in the state of Missouri, by profession (n=16) and year (2009-2016). Standard errors are clustered at the profession level (n=16). *, **, and *** indicate two-tailed statistical significance at the p<0.1, p<0.05, and p<0.01 levels, respectively.

	Count Models: DV = # of Tax Noncompliance Cases per Year per Profession				
Profession Level Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Ln(Workers in Profession)	1.782***	1.856***	1.757***	1.699***	1.692***
	[4.339]	[6.211]	[6.022]	[5.972]	[5.991]
% Self-Employed	7.564***	8.908***	7.298***	2.199	5.767**
	[3.437]	[3.968]	[3.016]	[0.860]	[2.498]
% Moved Recently	4.565	3.666	4.109	3.577	3.063
	[0.676]	[1.229]	[0.887]	[0.759]	[0.708]
Ln(Median Wages)	-1.109*	-1.407***	-0.794*	-0.540*	-0.572**
	[-1.691]	[-3.477]	[-1.697]	[-1.959]	[-2.005]
% who worked ≥ 40 weeks in prior year	3.248				
	[0.270]				
% who worked ≥ 48 weeks in prior year		7.327*			
		[1.911]			
Median Hours Worked in prior week			-0.035		
			[-0.547]		
% with Employer provided health insurance				-5.366***	
				[-2.633]	
% with Employer provided health insurance (excluding Self-employed)					-4.483***
					[-2.957]
Constant	-5.076	-5.492	-4.064	-3.564	-3.745
	[-0.610]	[-1.181]	[-1.027]	[-1.282]	[-1.362]
Observations	128	128	128	128	128
Pseudo R^2	0.097	0.103	0.097	0.107	0.108

Table 5

Table 5 reports negative binomial count models that predict the number of income tax noncompliance related professional license suspensions in the state of Missouri, by profession (n=16) and year (2009-2016). Standard errors are clustered at the profession level (n=16). *, **, and *** indicate two-tailed statistical significance at the $p<0.1$, $p<0.05$, and $p<0.01$ levels, respectively.

	Count Models: DV = # of Tax Noncompliance Cases per Year per Profession					
Profession Level Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ln(Workers in Profession)	1.641***	1.700***	1.772***	1.697***	1.655***	1.649***
	[7.432]	[4.833]	[6.673]	[6.252]	[6.125]	[6.149]
Ln(1+Suspensions in Other Professions)	-0.484***	-0.478***	-0.404**	-0.480***	-0.357*	-0.352*
	[-2.744]	[-2.591]	[-2.159]	[-2.630]	[-1.763]	[-1.726]
% Self-Employed	8.065***	7.922***	8.971***	7.709***	2.906	6.208***
	[3.889]	[3.815]	[4.313]	[3.590]	[1.241]	[3.010]
% Moved Recently	3.993	4.9	3.982	4.75	3.98	3.492
	[1.052]	[0.830]	[1.376]	[1.123]	[0.892]	[0.849]
Ln(Median Wages)	-0.860***	-0.999*	-1.300***	-0.718*	-0.515**	-0.545**
	[-2.846]	[-1.702]	[-3.497]	[-1.756]	[-1.983]	[-2.035]
% who worked ≥ 40 weeks in prior year		2.59				
		[0.247]				
% who worked ≥ 48 weeks in prior year			6.531*			
			[1.833]			
Median Hours Worked in prior week				-0.034		
				[-0.616]		
% with Employer provided health insurance					-4.968**	
					[-2.498]	
% with Employer provided health insurance (excluding Self-employed)						-4.146***
						[-2.798]
Constant	-1.041	-2.361	-3.056	-1.772	-1.806	-1.988
	[-0.312]	[-0.320]	[-0.697]	[-0.448]	[-0.657]	[-0.723]
Observations	128	128	128	128	128	128
Pseudo R^2	0.101	0.101	0.105	0.101	0.110	0.110

Table 6

Table 6 reports negative binomial count models that predict the number of income tax noncompliance related professional license suspensions in the state of Missouri, by profession (n=14) and year (2009-2016). This analysis excludes massage therapists and LPNs, two professions that are outliers in the primary analysis. Standard errors are clustered at the profession level (n=14). *, **, and *** indicate two-tailed statistical significance at the $p<0.1$, $p<0.05$, and $p<0.01$ levels, respectively.

	Count Models: DV = # of Tax Noncompliance Cases per Year per Profession						
Profession Level Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Ln(Workers in Profession)	1.468***	1.470***	1.457***	1.371***	1.435***	1.508***	1.501***
	[11.839]	[11.617]	[11.704]	[10.770]	[12.292]	[8.219]	[8.532]
Ln(1+Suspensions in Other Professions)	-0.013	-0.033	-0.051	-0.112	-0.046	-0.045	-0.033
	[-0.056]	[-0.157]	[-0.253]	[-0.600]	[-0.225]	[-0.222]	[-0.158]
% Self-Employed	5.594***	5.953***	6.049***	5.790***	5.489***	2.628	4.825***
	[3.407]	[3.349]	[3.275]	[3.183]	[2.892]	[1.400]	[3.226]
% Moved Recently	7.903**	7.199**	6.246**	1.441	5.992**	5.512*	5.423*
	[2.263]	[2.300]	[2.108]	[0.358]	[1.977]	[1.753]	[1.822]
Ln(Median Wages)		-0.004					
		[-0.808]					
Median Wages (in thousands)			-0.321			-0.145	-0.16
			[-1.009]			[-0.495]	[-0.531]
Median Income-to-poverty Ratio				-0.005			
				[-1.520]			
% on Welfare					11.611		
					[0.919]		
% with Employer provided health insurance						-3.228*	
						[-1.841]	
% with Employer provided health insurance (excluding Self-employed)							-2.770**
							[-2.198]
Constant	-12.234***	-11.868***	-8.298**	-7.828***	-11.725***	-8.021***	-8.200***
	[-5.523]	[-5.952]	[-2.376]	[-3.218]	[-6.602]	[-2.763]	[-2.807]
Observations	112	112	112	112	112	112	112
Pseudo R^2	0.104	0.105	0.106	0.108	0.106	0.111	0.111