Nonstandard Work Arrangements across Metropolitan and Nonmetropolitan Areas of the United States

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ABSTRACT

We examine the changes in prevalence of contingent and alternative work arrangements within the United States across metropolitan and non-metropolitan areas using the Current Population Survey (CPS) Contingent Worker Supplement (CWS) 1995, 1997, 1999, 2001, 2005, and 2017. We expand on a replication of the work done by McLaughlin and Coleman-Jensen (2008), by performing multivariate logistic regressions to describe the relationship between work arrangements and geographic area net of demographic and employment specific characteristics to identify how these relationships change across metropolitan status. We find evidence, in contrast of the prior work that situates contingent work as a largely rural process, of contingent work prevalence in urban spaces as well as significant differences across the CPS definitions of nonstandard work. On-Call Work remains a rurally located form of work, but independent contractors, temporary help agency workers, and workers provided by contract firms are more prevalent in urban spaces. Whereas those identified as contingent workers varies across size of metropolitan area. Our analysis suggests that using more specific definition of contingent and alternative work arrangements highlights the spatial distribution of these work types.

Keywords: Nonstandard Work, Urban, Rural, Contingent Work

1 INTRODUCTION

Job security remains a crucial issue for workers within the United States. With the rise of the online gig economy through firms like Uber, Lyft, TaskRabbit, AirBnB, Rover, and many more, interest has been reinvigorated in the subject of nonstandard work arrangements (Hollister (2015), Kalleberg and Dunn (2016)) and the limited security that is associated with these arrangements. ~~This interest is not new.~~ While many continue to be fascinated with the growth and development of the online gig economy, previous work have already identified and studied the category of work which these new firms fall into. The range of topics of interest across this space is vast but at the root of this research is a desire to describe and contextualize the state of nonstandard work across rural and urban spaces in the United States (Slack (2010), Haley-Lock (2012), Smith and Glauber (2013)). We contribute findings into the distribution of nonstandard workers using more recent measures than previous research in this field to capture the role of the gig economy into the broader layout of nonstandard work arrangements as well as the current layout of nonstandard work in the U.S..

The term "nonstandard work" includes a wide variety of organizational structures each with varied characteristics. The Current Populations Survey's Contingent Worker Supplement has been a primary measuring tool of nonstandard work within the United States for the past twenty years. The CWS defines five categories of nonstandard work: contingent workers, independent contractors, on-call workers, temporary help agency workers, and workers provided by contract firms. These five categories were established in 1995 and remain as descriptions for nonstandard work, while this is not an ideal characterization of nonstandard work given the suspicion around a changing climate of nonstandard work with the advent of gig economy labor, we use these definitions to measure nonstandard work evenly through time. The Bureau of labor Statistics bundles the last four terms into a separate group called alternative work arrangements (AWAs). Across these five categories and the many combinations of them which exist, we can imagine a plethora of styles of work and the consequences resulting from them. In 2017, 5.9 million people held contingent jobs, 10.6 million were independent contractors, 2.6 million were on-call workers, 1.4 million were temporary help agency workers, and 933,000 were provided by contracting firms (BLS (2018)). These terms are not mutually exclusive and may vary in identification across space.

Each one of these categories represent real people operating in a work environment external to many of the traditional social supports and protections intrinsic to standard work arrangements. Hyman (2018) describes the process by which many of these styles of work were created. Many of these exemptions from the norm of worker support are a result of prejudice and manipulation of exemptions (Hyman (2018)). This pocket of organizational structure has often been a source of reorganization within firms as workers are classified in such a way to avoid increasing costs. In addition, Katz and Krueger (2016) identify AWAs as one of the most significant sources of employment growth in the United States today, accounting for 94 percent of the net employment growth from 2005 to 2015.

The gig economy, while representing a considerably smaller portion of AWAs, is a rapidly growing subset (Michel (2018)). The growth of these firms and the number of people seeking employment across the gig economy, both as a primary and a supplementary source of income, have resulted in a variety of benefits and costs. Many of the new work arrangements offered by the gig economy come with greater flexibility regarding the number of hours worked, which could result in welfare improving bundles of leisure and consumption. On the other hand, workers within the gig economy are generally classified as independent contractors, preventing access to institutional protections such as the Fair Labor Standards Act.

The changing landscape of work or the changing definition of what it means to be employed requires a thorough investigation into the details of what this work looks like and if it exhibits any systematic patterns. Motivating this research is a supposed shift in viability and prevalence of contingent work in urban located occupations (Connelly and Gallagher (2004), Kalleberg (2009), ILO (2016)). While alternative work arrangements and contingent work have historically been related to seasonal and low-wage work associated with rural spaces, the growth in nonstandard work for urban locales suggests a recent change in the precarity that comes with nonstandard work. The availability of new technologies and the volume of freelance work allows for this growth

(Katz and Krueger (2016)). Additionally, firms have found increasing value in cutting labor costs by hiring temporary workers while maintaining a core group of full-time workers (George and Chattopadhyay (2015)). All these forces have combined to create what appear to be divergent trends among administrative and survey sources of data on how many people are engaging in nonstandard work (Abraham et al. (2018)).

To address this question, we begin with a replication of the work by McLaughlin and Coleman-Jensen (2008). Following the replication and identification of areas to improve, we investigate the spatial relationship of nonstandard work using a finer measurement of nonstandard work across urban and rural classification. This research describes the spatial distribution of nonstandard work using more recent data and stronger modeling.

2 DATA

The data used for this project comes from the Current Population Survey Contingent Worker Supplement. This survey is intended to answer the question of how many individuals participate in a form of either contingent or temporary work which that individual does or participates in without expecting continuing employment. This is done in conjunction with the CPS and has a universe of household members older than 15 who have worked for pay during the reference week or looked for work during the previous year. This supplement has been collected since February 1995, but it is not annual. The times of collection are February 1995, February 1997, February 1999, February 2001, February 2005, and May 2017. For the purposes of this analysis we utilize all this data as sourced from the CPS Supplement Files at the National Bureau of Economic Research.

The May 2017 Contingent Worker Supplement is the first edition of the supplement in twelve years and it provides a critical piece of understanding patterns in contingent work that have been suggested by several authors using smaller or disparate datasets (Katz and Krueger (2016); ILO (2016)). This data opportunity affords clarity for researchers, but also prompted this project to make some concessions within the data for setting up our covariates of interest. The original coding for race, industry, and region are not consistent with many categories in more recent versions of the supplement (2005, 2017), therefore, to merge the datasets we deferred to the less descriptive explanations of variables to maintain consistency.

This analysis is centered on five different variables which categorize nonstandard work. Nonstandard work is often a flexible term and can be applied to numerous types of work arrangements. We define the variables explicitly below. The definitions of these dependent variables are derived directly from the CPS. These terms maintained their definitions across the datasets merged for our analysis, however, respondent treatment of the definitions may have qualitative differences across time and industry. The nonstandard work terms used in our analysis denote respondents' primary job and does not include nonstandard work as secondary or supplemental sources of income. The definitions of nonstandard work are not mutually exclusive, so some independent contractors may also be contingent workers. An analysis of one category may resemble the analysis of another then as some correlation across observations under the same employment tag will exist, but each definition represents a specific feature of the nonstandard labor market. In addition to the five categories of nonstandard work, we identify and define the variables we are interested in exploring in relation to nonstandard work.

2.1 Variable Definition

Dependent Variables

Contingent Worker Workers who do not expect their jobs to last. Wage and salary workers are included even if they already have held the job for more than 1 year and expect to hold the job for at least an additional year. The self-employed and independent contractors are included if they expect their employment to last for an additional year or less and they had been self-employed or independent contractors for 1 year or less.

Independent Contractor Workers who are identified as independent contractors, independent consultants, or freelance workers, regardless of whether they are self-employed or wage and salary workers.

On-Call Worker Workers who are called to work only as needed, although they can be scheduled to work for several days or weeks in a row.

Temporary Help Agency Worker Workers who are paid by a temporary help agency, whether or not their job is temporary.

Workers Provided by Contract firms Workers who are employed by a company that provides them or their services to others under contract, are usually assigned to only one customer, and usually work at the customer's worksite.

Independent Variables

Urban Identifies the metropolitan status of a survey observation. Areas of population less than 100,000 are coded as nonmetropolitan or not identified.

Metro Size Identifies the population within one of seven ranges of values. Not identified or less than 100,000, 100,000-249,999, 250,000-499,999, 500,000-999,999, 1,000,000-2,499,999, 2,500,000-4,999,999, and 5,000,000+

Full-Time Identifies individuals as either full-time or part time conditional on being in the labor force.

Average Hours Sum of responses to "how many hours per week do you usually work at your main job" and "how many hours per week do you usually work at your other (job/jobs)"

Education Highest level of school completed, ranging from less than 1st grade to doctorate degrees.

Age The age of the respondent

Year What year the respondent was surveyed

Industry Code Major industry code (NAICS)

Health Insurance Response to "Do you have health insurance from any source?"

Employer Health Insurance Response to “Do you receive this health insurance through your employer?”

Race The race of the respondent

Region The geographic region of the respondent

Sex Identification of responded as either male or female

3 METHODS

We use logistic regression to estimate the log-odds that any given respondent is engaging in one of our five definitions of nonstandard work as a function of the geographic, demographic, and employment specific characteristics identified in the variable definition subsection. We perform a series of tests on our logistic regression and other variants for model selection which can be found in the appendix. Our selected covariates derive from prior work in this area as well as the replication we performed on the paper using 1999 and 2001 CWS data.

The replication looks back at McLaughlin and Coleman-Jensen (2008) which investigates a similar question of the prevalence of rural and urban nonstandard work, but under a different guiding assumption that nonstandard work is a rural process. That article attempted to describe how nonstandard work becomes related to rural spaces based on demographic and employment characteristics. Our research investigates the theory that nonstandard work is increasingly becoming associated with urban work. This article orients our own analysis.

3.1 Replication

The replication of McLaughlin and Coleman-Jensen (2008) required that we make approximations based on their results. Our replication results is based on the same pooled data from the 1999 and 2001 Contingent Worker Supplements used in the original analysis, and we approach the same sample size using list-wise deletion (n = 87,341) which is near to the McLaughlin and

Coleman-Jensen sample size (n = 85,838). [1]

Their paper uses logistic regression to evaluate the prevalence of contingent work status across urban and rural space to examine composite measures of their own design. These measures are nonstandard work, the widest definition created by McLaughlin and Coleman-Jensen to capture those who work part-time, on varied hours, or in contingent working arrangements. Non-metro nonstandard work is the subset of nonstandard workers just in rural areas which is measured as areas with a population with less than 100,000 or not identified. Respondents who chose not to be identified by location are considered rural in this analysis, which may lead to some bias in the spatial component of the analysis. Contingent work is based on the generic definition provided by the Current Population Survey. Part-time work is defined as working less than 35 hours per week. Varied Work is defined as workers employed in jobs where the hours may vary each week. All of these definitions are interested in a respondent's primary job.

The original findings of the paper provide evidence that nonstandard work is a largely rural process and will continue to be so for years to come. There are industry and occupational differences that are related to higher probability of nonstandard work. The replication supports these findings and suggests that given our slightly larger sampling frame, that supposed regional differences may not be as useful as previously believed. The replication also finds weaker evidence for differences in nonstandard work between educational attainment groups. The replication findings prompt our expansion so that we can investigate differences with more recent data. Since the time of the McLaughlin and Coleman-Jensen data, the Great Recession occurred, the Affordable Care Act passed, and the gig economy established itself as a viable means of work.

3.2 Expansion

The results of the replication are provided in the Table 1 and Figure 1. Our replicated point estimates and signs approximate the original paper fairly well. The replication estimates pointed

[1] We suspect the difference here is based on the vagueness of the word "recent" in their covariate measuring recent job loss and the recoding of healthcare variable, as the original paper has a covariate to capture if I respondent "can access healthcare from source other than respondent's employer" which is different than the codebook which asks if respondents does have healthcare from another source than their employer.

out the usefulness and lack thereof for a few of the key covariates for our expansion using new data. The usage of the right-to-work state covariate does not seem related to nonstandard work across urban and rural spaces in the original paper or our replication. Moreover, the logic behind controlling for right-to-work laws does not offer much explanatory power as we generally expect unionized jobs to be far different than nonstandard work and for right-to-work states to be highly correlated with states and regions with large rural areas especially in 1999 and 2001. The covariates in the original paper for age and education were recoded into groupings that do not offer avenues for deeper analysis. For instance, the referent category for age is 24-54; while this may make sense colloquially, it misses the opportunity to investigate the largest part of the workforce.

To connect our replication to the expansion on the 2017 CWS data, we used the estimates provided by the replication to try to predict the new data. The percent correctly predicted from the replication is compared to the predictions of the new data. While the replication model estimates seems to do a solid job of predicting the 2017 outcomes (Table 4), the replication estimates are exposed as only being a percent correctly predicted of 60.6% on the subset of non-metro nonstandard workers. This inability to predict the new data along the spatial subset provides initial insight into our findings that the spatial relationship of nonstandard work may have changed since 2001. This percent correctly predicted value points to the notion that nonstandard work may not be changing as far as the percentage of the population who have nonstandard work as their primary job, but where these people reside has changed.

3.3 Validation

Next, we ran our own logistic regression model with different selected covariates outlined above. First, our model improves on the fit of McLaughlin Coleman-Jensen (2008) model as demonstrated by the area under the curve of ROC plots (Figure 17) illustrating the predictive capabilities of the only dependent variable our papers share: contingent work status. Our model has a greater area under the curve with fit of .83 compared to .78 for Mclaughlin and Coleman-Jensen. The key differences in our analysis lies in the more specific outcomes of interest and the more parsimonious covariates used to make sense of nonstandard work in rural and urban spaces.

We improve on the design of the McLaughlin and Coleman-Jensen piece by investigating five binary outcomes that allow us to show the within group differences between rural and urban nonstandard employees. These types of nonstandard work are based on CWS definitions: contingent employees, independent contractors, temporary workers, contract firm workers, and on-call workers. We selected logistic regression to delve into the question of how these employment types are spatially distributed to most directly answer our question.

We validated our results by creating a test set and training set to evaluate the model fit. We split our sample (n = 263,326) in half by randomly selecting observations from the full sample using the R package dplyr's sample_frac function then measured performance of the model using the package ROCR. Next, we fit our model to the training set. We use these estimates to predict the test set. Our model's AUC values for the training set, test set, and full data are provided in the Table 4.

4 RESULTS

The primary thrust of this analysis was to explore how these nonstandard work arrangements vary across urban and rural spaces. As can be seen in table 2, the five categories of nonstandard work vary in their relationship to identified population size of respondents regions. Table 2 presents the log-odd coefficients of each individual logit model for our five nonstandard work categories. We have break the binary rural/urban variable into the component parts and instead identify across metropolitan population size categories. Treating those respondents from either unidentified regions or regions with fewer than 100,000 people as the reference category, we can estimate how an increase in the local population relates to the prevalence of nonstandard work.

We find that contingent workers are somewhat inconsistent in relation to urbanization as the sign varies as population increases. These estimates are also not consistently significant at the 95 percent level. This is in contrast to independent contractors, temporary help agency workers, contract company workers, and on-call workers. We find that a respondent's log-odds of being an independent contractor increase as population size increases. This also holds true for temporary help agency workers, and workers provided by contract firms. On-Call workers on the other hand are significantly more likely to be present in less urbanized spaces.

While we found significant differences within classification across urban and rural spaces for some categories, the scale of this difference seemed less substantial than the difference across industry. The respondent's industry seemed to be a significant level shifter with regards to the employment of nonstandard workers, outweighing variation caused by urbanization. This can be seen in figures 7-11 in the appendix. Some notable examples of this is the dramatic increase in an individuals likelihood of being a temp worker by entering the Business, Auto, and Repair industry. One explanation of the significance of industry is that norms across industries translate over these geographic spaces. Workers and firms engaged in an industry may be more likely to adopt similar practices regardless of level of urbanization. It is unclear if this is due to economic pressures within industry, social pressure to mimic, or some other reason.

Beyond the urban/rural relationship across these categories, one goal was to estimate the value of the label ”nonstandard employment.” By exploring the individual identifiers we are able to see some common threads and through these commonalities improve the prediction process of which respondents engaged in nonstandard work. If we utilize these models to predict a respondent as participating in any one of these categories we are left with a slightly disappointing result. We find little improvement in our predictive power given the models. This remains the result whether we use individual categories or pooled categories of nonstandard work. Using a combination of contingent workers and independent contractors we found no substantial improvement in prediction, as can be seen in Table 1 below. Further tests of the effectiveness of the prediction across these categories via ROC plots and Actual v. predicted plots are included in the appendix.

5 CONCLUSIONS

Our analysis illustrates that the urban and rural distribution of nonstandard work is more mixed when we use more specific definitions of nonstandard work. The log-odds of general contingent work does not seem to significantly differ across rural and urban space. For independent contractors, temporary help agency workers, and workers provided by contract firms, living in an urban space

Dependent Variable	Assuming Probability of Zero	Model Prediction
Contingent	0.9581	0.9589
Indep. Cont.	0.9767	0.9808
Temporary	0.9909	0.9914
Cont. Comp.	0.9938	0.9938
On-Call	0.98	0.9799
Contingent/ind. cont.	0.936	.94

Table 1. Percent correctly predicted given an assumption that nobody participates in that work arrangement and the models.

is associated with an increase in the log-odds of having those work statuses. Whereas on-call workers have a decrease in the log-odds of being on-call if they live in an urban space. These results point to the value of specificity in assessing contingent work status. Prior work in this area has relied on aggregate measures that have mischaracterized the spatial distribution on nonstandard work. The addition of the 2017 CWS allows this research to support an alternative theory to the one proposed in McLaughlin and Coleman-Jensen (2008). They proposed that nonstandard work would remain associated with rural life. Our data suggest, in union with recent work, that the rural association with nonstandard work may be waning. However, this suggestion is based on some potentially biased responses. Rather surprisingly, the CWS suggests a relatively flat percentage of U.S. workers in nonstandard arrangements across nearly twenty years, with the population in nonstandard work hovering around 6.9% from 1995 to 2017. We remain cautious about our findings here as the evidence from tax data and other surveys instruments present a quickly increasing amount of nonstandard work in the U.S. This discrepancy may be attributed to how the questions devised for the 1995 CWS installment may need to shift to change with more contemporary definitions of nonstandard work, or there may need to be more focus toward the qualitative difference between what counts as a primary job in the minds of American workers.

Beyond our reservations about the dataset, we propose that this research illustrates a marker of change in the distribution of nonstandard work. By delving into more specific measurements of AWAs and contingent work, we provide insight into the within group variation of nonstandard workers. The prevalence of urban nonstandard work supports theories that firms are restructuring to cut down on labor costs (George and Chattopadhyay (2015), ILO (2016)), the implementation of the Affordable Care Act offers some more viability to nonstandard work that was not previously available, and the spatial distribution of people with low human and economic capital are becoming concentrated in cities (Smith and Glauber (2013), Katra and Baron (2015)). At the onset, we suspected that the redefinition of nonstandard work because of the gig economy would be related to a shift in nonstandard work to urban spaces, but it may be the case that large trends are more reliable explanations of our findings.

Future work should build on this contribution by investigating the qualitative differences in what our five outcomes mean to workers across different spaces and industries. The precarity of nonstandard work is known to researchers, how this is distributed under our current typologies across urban and rural areas is largely hidden. As it stands, it is difficult to negotiate bias that is built into the respondent feelings toward questions of what constitutes primary jobs. Perhaps primary jobs are aspirational rather than monetarily driven. Moonlighting as an Uber driver may supplement the bills, but this is not how many would describe their line of work. Additionally, the CWS should craft questions to get at gig economy work more directly. Lastly, it may be the case that contingent work is too wide a definition. We need to be aware of how loosely the variety of jobs built into this definition can be when considering the inequality associated with the term.

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6 APPENDIX

Table 2. Logit models of the five categories of nonstandard work

	Dependent variable:				
	Contingent	Indep. Cont.	Temporary	Cont. Comp.	On-Call
	(1)	(2)	(3)	(4)	(5)
100,000 - 249,999	0.010	0.108	0.334^{***}	0.170	-0.227^{***}
	(0.050)	(0.074)	(0.118)	(0.127)	(0.067)
250,000 - 499,999	-0.089^{*}	0.069	0.467^{***}	-0.039	-0.208^{***}
	(0.048)	(0.074)	(0.103)	(0.127)	(0.063)
500,000 - 999,999	-0.080^{*}	0.252^{***}	0.443^{***}	-0.083	-0.246^{***}
	(0.042)	(0.060)	(0.097)	(0.114)	(0.057)
1,000,000 - 2,499,999	-0.054	0.147^{***}	0.526^{***}	0.229^{**}	-0.287^{***}
	(0.038)	(0.056)	(0.086)	(0.095)	(0.051)
2,500,000 - 4,999,999	0.148^{***}	0.149^{**}	0.560^{***}	0.508^{***}	-0.293^{***}
	(0.045)	(0.065)	(0.100)	(0.102)	(0.066)
5,000,000+	0.043	0.260^{***}	0.550^{***}	0.443^{***}	-0.253^{***}
	(0.035)	(0.054)	(0.083)	(0.089)	(0.049)
Full_time	1.057^{***}	0.321^{***}	0.026	0.176^{**}	1.276^{***}
	(0.028)	(0.041)	(0.064)	(0.087)	(0.038)
Avg_hours	0.071^{***}	0.007^{***}	0.077^{***}	0.058^{***}	0.057^{***}
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Education	0.092^{***}	0.092^{***}	0.045^{***}	0.078^{***}	0.023^{***}
	(0.005)	(0.007)	(0.011)	(0.013)	(0.007)
Age	-0.012^{***}	0.022^{***}	0.001	0.005^{**}	0.012^{***}
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Year	-0.012^{***}	0.041^{***}	-0.042^{***}	-0.026^{***}	-0.004^{*}
	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
Has Health Insurance	-1.219^{***}	2.607^{***}	-15.260	-14.224	-15.298
	(0.127)	(0.058)	(154.917)	(159.232)	(98.166)
Health Insurance via Employer	-1.177^{***}	-1.746^{***}	-2.500^{***}	-0.477^{***}	-0.941^{***}
	(0.033)	(0.063)	(0.089)	(0.071)	(0.045)
American_Indian_Aleut_Eskimo	0.378^{**}	-0.078	-0.603^{*}	-0.497	-0.083
	(0.149)	(0.237)	(0.324)	(0.372)	(0.195)
Asian_Pacific_Islander	0.366^{***}	-0.191	-0.260	0.050	-0.538^{***}
	(0.130)	(0.175)	(0.254)	(0.274)	(0.177)
Black	0.117	-0.035	0.309	-0.341	-0.250
	(0.126)	(0.165)	(0.233)	(0.268)	(0.160)
White	-0.084	0.146	-0.505^{**}	-0.541^{**}	-0.271^{*}
	(0.120)	(0.151)	(0.226)	(0.254)	(0.150)
Northwest	0.147^{***}	0.046	-0.119	-0.230^{**}	0.054
	(0.037)	(0.058)	(0.081)	(0.094)	(0.053)
South	0.103^{***}	0.152^{***}	-0.066	0.103	0.146^{***}
	(0.034)	(0.050)	(0.070)	(0.078)	(0.046)
West	0.271^{***}	0.258^{***}	-0.194^{***}	-0.008	0.339^{***}
	(0.033)	(0.051)	(0.075)	(0.082)	(0.045)
Female	-0.193^{***}	-0.150^{***}	0.442^{***}	-0.578^{***}	-0.301^{***}
	(0.026)	(0.039)	(0.054)	(0.066)	(0.036)
Constant	17.990^{***}	-95.726^{***}	91.942	58.420	18.100
	(3.839)	(5.479)	(155.135)	(159.460)	(98.294)
Industry Controls	Yes	Yes	Yes	Yes	Yes
Observations	212,959	212,959	212,959	212,959	212,959
Log Likelihood	$-29{,}238.140$	$-14{,}352.870$	$-6{,}904.771$	$-6{,}737.222$	$-17{,}622.980$
AIC	58,576.280	28,805.740	13,909.540	13,574.440	35,345.960
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 3. Percent Correctly Predicted, McLaughlin and Coleman-Jensen's model on the 2017 CWS

	Work Conditions	1999-01	2017
1	Nonstandard Work	0.694	0.706
2	Non Metro Area	0.920	0.606
3	Contingent	0.982	0.988
4	Part-time	0.848	0.781
5	Varied Work	0.923	0.943

Table 4. AUC Values for Cross-Validation

Worker Status	Training Data	Test Data	Full Data
Independent Contractors	0.910	0.906	0.901
Contingent Worker	0.819	0.821	0.822
Temporary Agency	0.927	0.926	0.906
Contract Firms	0.822	0.810	0.824
On-Call Worker	0.812	0.813	0.819

Figure 1. McLaughlin and Coleman-Jensen (2008) Results

Table 3. Logistic Regression Models Predicting the Likelihood of Being a Nonstandard, Contingent, Part-time, or Varied Hour Worker

	Model 1 Overall Nonstandard Work		Model 2 Nonmetro Nonstandard Work		Model 3 Contingent Work		Model 4 Part-Time Work		Model 5 Varied Hour Work	
	Parameter Estimates	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*
Intercept	−3.14***		−2.66***		−4.29***		−4.70***		−3.11***	
Residence (Reference: Nonmetro)										
Central City	−0.15***	0.86	-	-	−0.21**	0.81	0.05	1.06	−0.38***	0.69
Suburban	−0.19***	0.83	-	-	−0.26***	0.77	0.02	1.02	−0.41***	0.66
Not Identified	−0.08*	0.92	-	-	−0.12	0.89	0.06	1.06	−0.22***	0.80
Employment Characteristics										
Industry (Reference: Public Administration)										
Agriculture	1.54***	4.66	1.01***	2.74	−0.06	0.94	1.51***	4.53	1.38***	3.97
Mining	0.97***	2.63	0.82***	2.28	−0.58	0.56	0.09***	1.09	1.13***	3.09
Construction	1.36***	3.89	1.11***	3.03	0.50***	1.64	1.22***	3.39	1.17***	3.22
Manufacturing	0.17***	1.19	−0.16	0.85	−0.65***	0.52	0.14***	1.15	0.26*	1.29
Transportation and Public Utilities	0.90***	2.46	0.82***	2.26	−0.60***	0.55	0.91***	2.50	0.99***	2.70
Wholesale Trade	0.52***	1.69	0.45***	1.57	−0.41**	0.66	0.71***	2.02	0.40**	1.49
Retail Trade	1.25***	3.51	1.00***	2.71	−0.46***	0.63	1.66***	5.28	0.74***	2.09
Finance, Insurance, and Real Estate	0.60***	1.82	0.47**	1.59	−0.73***	0.48	0.77***	2.16	0.62***	1.86
Low-end Services[A]	1.36***	3.90	1.22***	3.40	0.59***	1.81	1.40***	4.05	1.12***	3.06
High-end Services[B]	1.07***	2.93	0.54***	1.72	0.24*	1.27	1.40***	4.05	0.56***	1.75
Occupation (Reference: Executive, Administrative, and Managerial)										
Professional Specialty	0.43***	1.53	0.40***	1.50	0.68***	1.97	0.54***	1.71	0.17**	1.19
Technicians and Related Support	0.35***	1.42	0.38*	1.47	0.26	1.29	0.55***	1.73	−0.10	0.91
Sales	0.53***	1.70	0.25*	1.28	0.07	1.08	0.67***	1.96	0.29***	1.34
Administrative support, including clerical	0.35***	1.41	0.35***	1.42	0.67***	1.96	0.69***	1.99	−0.43***	0.65
Service	0.94***	2.56	0.84***	2.32	0.21	1.23	1.30***	3.66	0.21***	1.24

Table 3. Continued

	Model 1 Overall Nonstandard Work		Model 2 Nonmetro Nonstandard Work		Model 3 Contingent Work		Model 4 Part-Time Work		Model 5 Varied Hour Work	
	Parameter Estimates	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*
Precision Production, Craft, and Repair	0.19***	1.21	0.09	1.09	0.36**	1.44	0.09***	1.09	−0.01	0.99
Operators, Fabricators, and Laborers	0.71***	2.03	0.56***	1.75	0.69***	1.99	0.85***	2.35	0.27***	1.31
Farming, Forestry, and Fishing	0.74***	2.09	0.96***	2.62	1.07***	2.91	0.36	1.43	0.52***	1.68
Can Obtain Health Insurance from Source Other than Employer	0.58***	1.79	0.50***	1.64	0.28***	1.32	0.75***	2.12	0.21***	1.23
Prior Job Loss	0.34***	1.40	0.58***	1.79	1.12***	3.08	0.16**	1.17	−0.11	0.90
Multiple Job Holder	0.43***	1.53	0.36***	1.43	0.15	1.16	0.81***	2.26	−0.38***	0.68
Right to Work State	−0.10**	0.90	−0.11*	0.89	−0.10	0.91	−0.06	0.94	−0.08*	0.92
Human Capital and Demographic Characteristics										
Educational Attainment (Reference: High School or GED)										
Less Than High School	0.18***	1.20	0.27***	1.32	0.13	1.14	0.21***	1.23	0.11*	1.11
Associates	−0.02	0.98	−0.08	0.93	−0.18*	0.83	0.10	1.10	−0.13*	0.87
Bachelors or higher	−0.04	0.96	−0.02	0.98	0.13*	1.14	−0.08	0.92	−0.04	0.96
Race (Reference: Non-Hispanic White)										
Non-Hispanic Black	−0.20***	0.82	−0.19*	0.82	0.20*	1.22	−0.33***	0.72	−0.06	0.94
Hispanic	−0.18***	0.84	−0.43***	0.65	0.19*	1.21	−0.21***	0.81	−0.23***	0.80
All Other	−0.18***	0.84	−0.25*	0.78	0.20	1.22	−0.18**	0.84	−0.21*	0.81
Age (Reference: 25–54)										
16–18	0.74***	2.09	0.42	1.52	0.31	1.36	1.08***	2.95	−0.05	0.95
19–24	0.07	1.08	0.06	1.07	0.28***	1.33	0.14**	1.15	−0.16**	0.85
55–64	0.44***	1.56	0.40***	1.49	−0.04	0.96	0.48***	1.61	0.38***	1.46
65+	1.88***	6.56	1.78***	5.92	0.69***	2.00	1.87***	6.52	0.95***	2.59
Female	0.67***	1.95	0.68***	1.97	0.13*	1.14	1.13***	3.10	−0.07*	0.93

Table 3. Continued

	Model 1 Overall Nonstandard Work		Model 2 Nonmetro Nonstandard Work		Model 3 Contingent Work		Model 4 Part-Time Work		Model 5 Varied Hour Work	
	Parameter Estimates	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*	*Parameter Estimates*	*Odds Ratios*
Citizenship (Reference: US Citizen US Born)										
US Citizen Foreign Born	−0.14**	0.87	−0.30	0.74	−0.10	0.90	−0.22***	0.80	0.04	1.04
Not US Citizen	0.08	1.08	0.16	1.17	0.67***	1.96	−0.15**	0.86	0.04	1.04
Region (Reference: New England)										
Mideast	−0.13**	0.88	−0.12	0.89	0.02	0.98	−0.15**	0.86	−0.06	0.94
Great Lakes	−0.16***	0.85	−0.33***	0.72	−0.08	0.92	−0.15*	0.86	−0.13	0.88
Plains	−0.27***	0.77	−0.24**	0.79	−0.07	0.93	−0.27***	0.76	−0.24**	0.79
Southeast	−0.16**	0.85	−0.25**	0.78	0.07	1.08	−0.42***	0.66	0.17**	1.18
Southwest	−0.21***	0.81	−0.17	0.85	0.08	1.09	−0.42***	0.65	0.08	1.09
Rocky Mountain	0.03	1.03	0.08	1.09	0.39***	1.48	−0.00	1.00	−0.12	0.88
Far West	−0.04	0.96	−0.07	0.93	0.25*	1.29	−0.05	0.95	−0.11	0.90
−2LL (df)	81196.25 (48)		15474.07 (45)		24322.24 (48)		54479.74 (48)		43101.64 (48)	
R^2_L	0.108		0.115		0.073		0.173		0.045	
	N=85838		N=19803		N=85838		N=85838		N=85838	

*Indicates the coefficient is statistically significant at p ≤ .05; **p ≤ .01; ***p ≤ .001.
Data are weighted to represent the U.S. population.
The models also control for marital status.
[A] Low-end Services include private households; business, auto and repair services; personal services; and entertainment and recreation services.
[B] High-end Services include hospitals; medical services; educational services; social services; and other professional services.

Table 1: Replication Results

	Dependent variable:				
	Nonstandard		Contingent	Part-time	Varied Work
	(1)	(2)	(3)	(4)	(5)
Central City	−0.113**		−0.229***	0.015	−0.341***
	(0.056)		(0.082)	(0.033)	(0.042)
Suburban	−0.149***		−0.265***	0.098***	−0.369***
	(0.050)		(0.073)	(0.029)	(0.035)
Not Identified	−0.067		−0.248***	0.026	−0.211***
	(0.058)		(0.087)	(0.034)	(0.041)
Agriculture	−0.528***	−1.297***	−0.658**	1.398***	1.252***
	(0.197)	(0.338)	(0.295)	(0.131)	(0.146)
Mining	−0.691**	−1.209***	−0.710	−0.257	1.040***
	(0.322)	(0.421)	(0.477)	(0.292)	(0.176)
Construction	−0.071	−0.463**	−0.038	0.589***	1.123***
	(0.113)	(0.204)	(0.169)	(0.092)	(0.101)
Manufacturing	−0.763***	−1.079***	−0.909***	−0.027	0.411***
	(0.108)	(0.196)	(0.168)	(0.083)	(0.098)
Transportation	−0.749***	−0.883***	−0.888***	0.693***	1.055***
	(0.122)	(0.224)	(0.189)	(0.083)	(0.099)
Wholesale	−0.573***	−0.720***	−0.697***	0.563***	0.531***
	(0.144)	(0.271)	(0.221)	(0.095)	(0.116)
Retail	−0.890***	−1.475***	−0.815***	1.420***	0.793***
	(0.106)	(0.199)	(0.156)	(0.074)	(0.095)
Finance	−0.886***	−1.352***	−0.963***	0.631***	0.637***
	(0.131)	(0.302)	(0.200)	(0.082)	(0.104)
Low-End Services	0.183*	−0.297*	0.186	1.155***	1.060***
	(0.095)	(0.177)	(0.143)	(0.074)	(0.093)
High-End Services	0.193**	−0.064	0.024	1.313***	0.610***
	(0.090)	(0.155)	(0.138)	(0.071)	(0.092)
Pro Specialty	0.728***	0.803***	1.044***	0.577***	0.177***
	(0.074)	(0.173)	(0.136)	(0.045)	(0.052)
Technician	0.321***	0.285	0.861***	0.578***	−0.064
	(0.120)	(0.272)	(0.190)	(0.067)	(0.090)
Sales	0.085	0.071	0.541***	0.691***	0.174***
	(0.099)	(0.231)	(0.159)	(0.047)	(0.055)
Admin and Clerical	0.699***	0.821***	1.227***	0.748***	−0.410***
	(0.078)	(0.173)	(0.136)	(0.043)	(0.058)
Services	0.083	0.106	0.467***	1.071***	0.150***
	(0.082)	(0.178)	(0.142)	(0.044)	(0.053)
Craft and Repair	0.459***	0.517***	0.884***	0.476***	0.047
	(0.081)	(0.174)	(0.141)	(0.048)	(0.050)
Fishing, Forestry, Farming	0.813***	0.660**	1.133***	0.352***	0.659***
	(0.180)	(0.317)	(0.278)	(0.122)	(0.122)

Access the Health Insurance	-0.949^{***}	-0.903^{***}	-1.050^{***}	-0.517^{***}	-0.467^{***}
	(0.043)	(0.086)	(0.060)	(0.028)	(0.034)
Multiple Jobs	0.202^{***}	0.154	0.201^{**}	0.666^{***}	-0.369^{***}
	(0.065)	(0.124)	(0.096)	(0.036)	(0.061)
Right To Work State	-0.105^{*}	-0.021	-0.161^{*}	-0.154^{***}	-0.098^{**}
	(0.057)	(0.097)	(0.084)	(0.034)	(0.041)
Less than HS Education	-0.062	0.067	-0.022	0.130^{***}	0.012
	(0.061)	(0.119)	(0.085)	(0.037)	(0.045)
Associates Degree	-0.228^{***}	-0.163	-0.171	-0.003	-0.080
	(0.073)	(0.134)	(0.109)	(0.037)	(0.050)
Bachelors and above	0.043	-0.041	0.050	-0.161^{***}	-0.021
	(0.053)	(0.118)	(0.083)	(0.031)	(0.038)
Black	0.209^{***}	0.380^{**}	0.265^{***}	-0.413^{***}	-0.119^{**}
	(0.064)	(0.183)	(0.095)	(0.041)	(0.052)
Latinx	-0.003	0.141	0.049	-0.407^{***}	-0.316^{***}
	(0.071)	(0.196)	(0.101)	(0.046)	(0.061)
All Other Races	0.267^{***}	0.338^{**}	0.278^{**}	-0.179^{***}	-0.173^{**}
	(0.080)	(0.167)	(0.118)	(0.056)	(0.073)
Age: 16-18	1.625^{***}	1.848^{***}	2.032^{***}	2.942^{***}	0.344^{***}
	(0.082)	(0.158)	(0.105)	(0.057)	(0.072)
Age: 19-24	1.051^{***}	1.212^{***}	1.355^{***}	1.024^{***}	0.045
	(0.047)	(0.095)	(0.064)	(0.029)	(0.045)
Age: 55-64	-0.080	-0.043	-0.294^{**}	0.431^{***}	0.415^{***}
	(0.067)	(0.133)	(0.119)	(0.033)	(0.039)
Age: 65+	0.738^{***}	0.931^{***}	0.187	1.897^{***}	1.081^{***}
	(0.087)	(0.160)	(0.173)	(0.045)	(0.053)
Female	0.050	-0.096	0.082	0.987^{***}	-0.066^{**}
	(0.040)	(0.086)	(0.061)	(0.024)	(0.030)
Foreign Born US Citizen	-0.113	-0.006	-0.120	-0.163^{***}	-0.029
	(0.103)	(0.355)	(0.162)	(0.060)	(0.075)
Non-US Citizen	0.514^{***}	0.322	0.475^{***}	-0.251^{***}	-0.063
	(0.071)	(0.262)	(0.103)	(0.054)	(0.067)
MidEast	-0.051	-0.272	-0.164	-0.094^{**}	-0.086^{*}
	(0.072)	(0.188)	(0.106)	(0.040)	(0.052)
Great Lakes	-0.184^{**}	-0.266^{*}	-0.228^{**}	-0.068^{*}	-0.128^{**}
	(0.076)	(0.155)	(0.111)	(0.041)	(0.054)
Plains	-0.080	-0.345^{**}	-0.020	0.050	-0.146^{**}
	(0.088)	(0.142)	(0.126)	(0.049)	(0.061)
SouthEast	-0.127	-0.420^{***}	-0.245^{**}	-0.321^{***}	0.148^{***}
	(0.080)	(0.136)	(0.117)	(0.045)	(0.054)
SouthWest	0.008	-0.339^{*}	-0.082	-0.240^{***}	0.010
	(0.092)	(0.175)	(0.135)	(0.055)	(0.067)
Rocky_Mountain	0.217^{**}	0.128	0.144	0.162^{***}	-0.144^{**}
	(0.086)	(0.135)	(0.124)	(0.050)	(0.065)
Far_West	0.090	-0.028	-0.074	-0.030	-0.098^{*}
	(0.073)	(0.155)	(0.108)	(0.043)	(0.055)
Constant	-2.800^{***}	-2.390^{***}	-3.844^{***}	-3.598^{***}	-2.614^{***}
	(0.130)	(0.236)	(0.207)	(0.091)	(0.110)
Observations	87,341	20,286	87,341	87,341	87,341
Log Likelihood	-13,574.530	-3,256.956	-6,998.062	-31,515.540	-22,650.190
Akaike Inf. Crit.	27,237.070	6,595.913	14,084.120	63,119.080	45,388.380

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

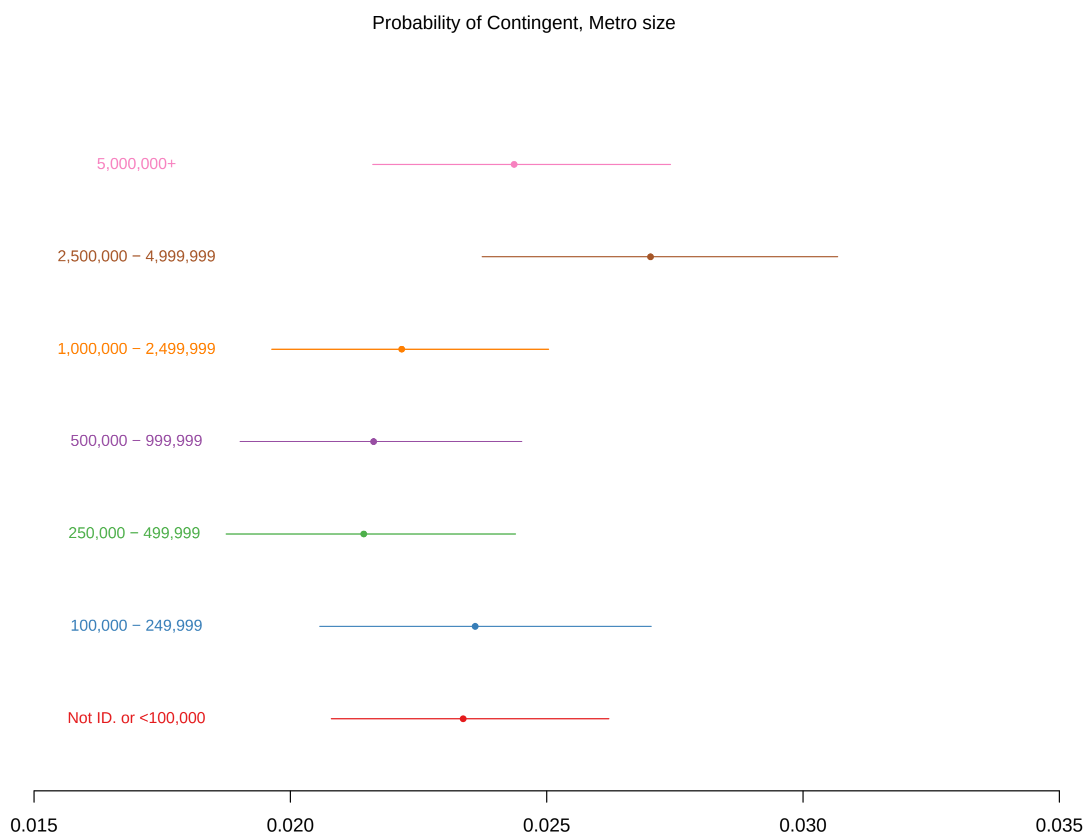
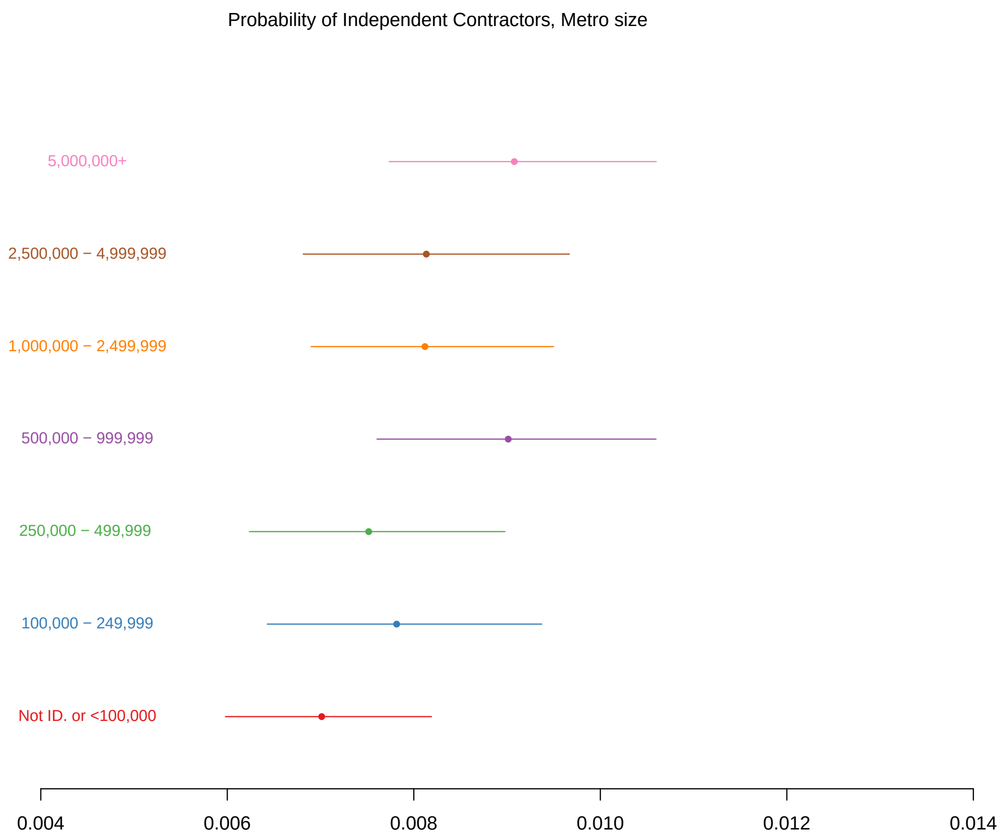

Probability of Contingent, Metro size
5,000,000+
2,500,000 − 4,999,999
1,000,000 − 2,499,999
500,000 − 999,999
250,000 − 499,999
100,000 − 249,999
Not ID. or <100,000
0.015
0.020
0.025
0.030
0.035

Figure 2



Probability of Independent Contractors, Metro size
5,000,000+
2,500,000 − 4,999,999
1,000,000 − 2,499,999
500,000 − 999,999
250,000 − 499,999
100,000 − 249,999
Not ID. or <100,000
0.004
0.006
0.008
0.010
0.012
0.014

Figure 3

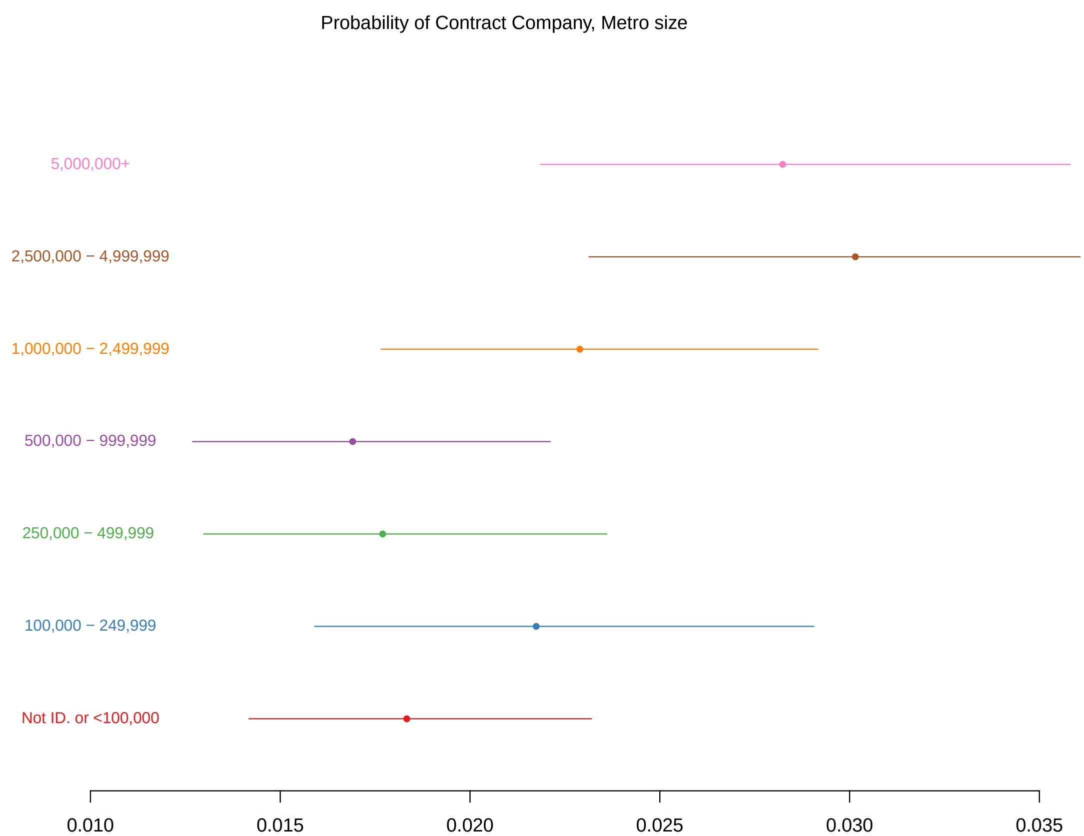

Probability of Contract Company, Metro size
5,000,000+
2,500,000 − 4,999,999
1,000,000 − 2,499,999
500,000 − 999,999
250,000 − 499,999
100,000 − 249,999
Not ID. or <100,000
0.010
0.015
0.020
0.025
0.030
0.035

Figure 4

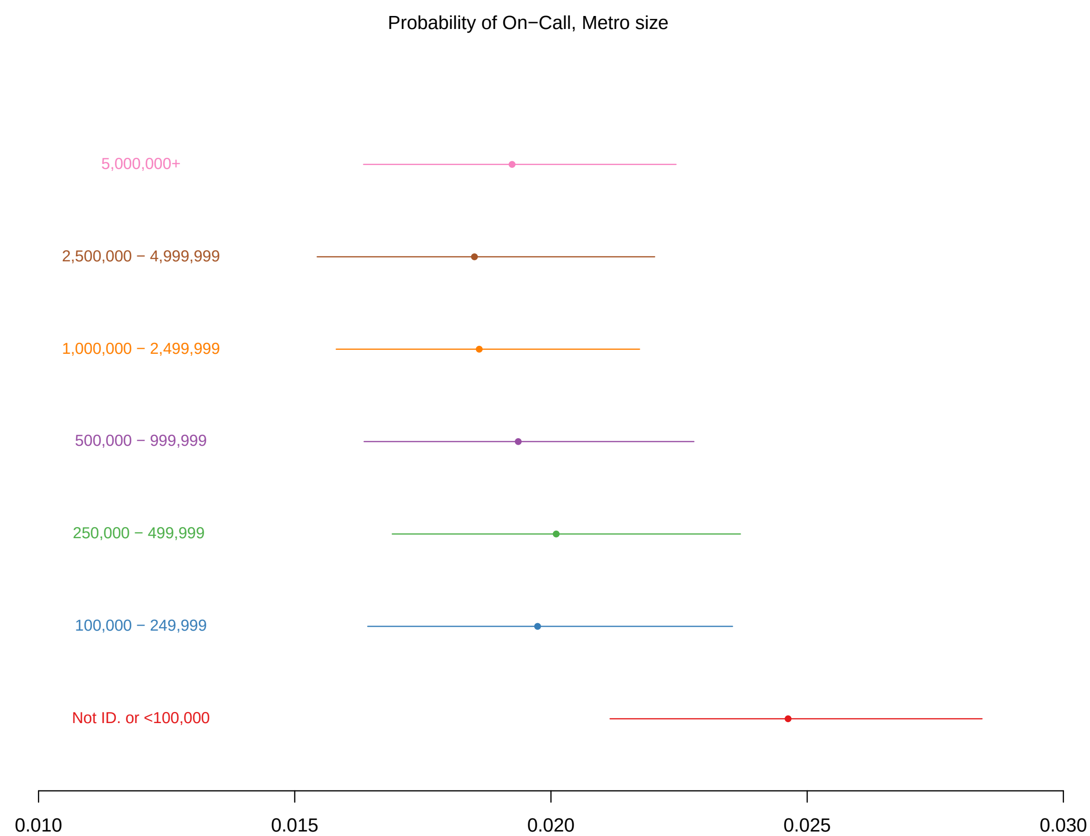

Probability of On−Call, Metro size
5,000,000+
2,500,000 − 4,999,999
1,000,000 − 2,499,999
500,000 − 999,999
250,000 − 499,999
100,000 − 249,999
Not ID. or <100,000
0.010
0.015
0.020
0.025
0.030

Figure 5

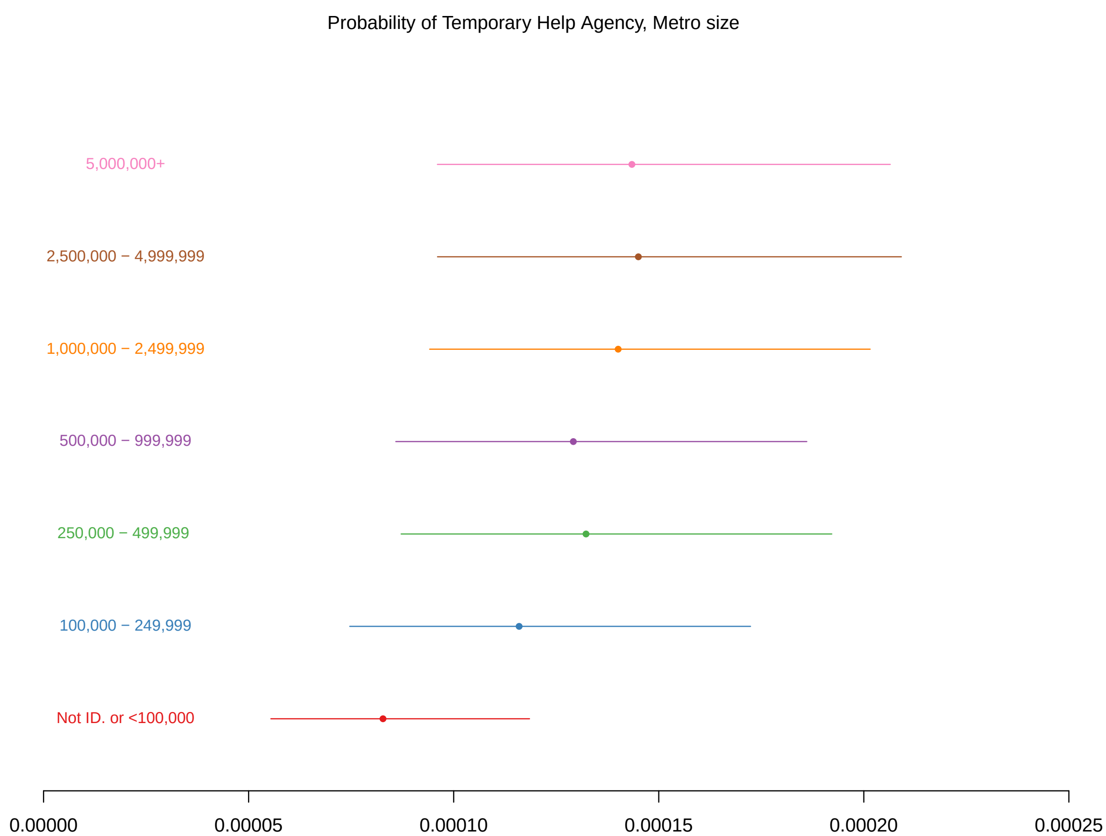

Probability of Temporary Help Agency, Metro size
5,000,000+
2,500,000 − 4,999,999
1,000,000 − 2,499,999
500,000 − 999,999
250,000 − 499,999
100,000 − 249,999
Not ID. or <100,000
0.00000
0.00005
0.00010
0.00015
0.00020
0.00025

Figure 6

Percent Contingent Workers, Industry

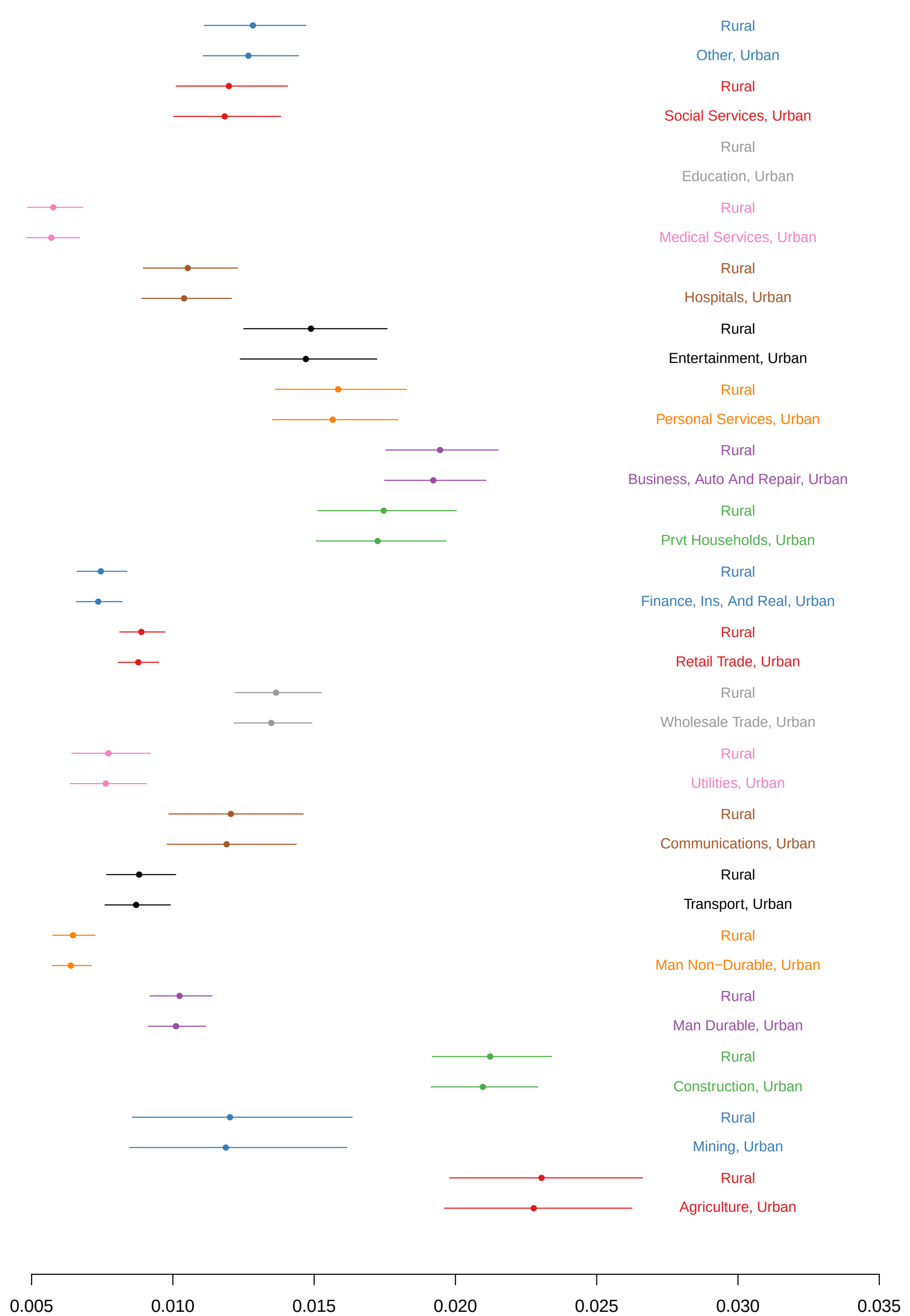


Figure 7

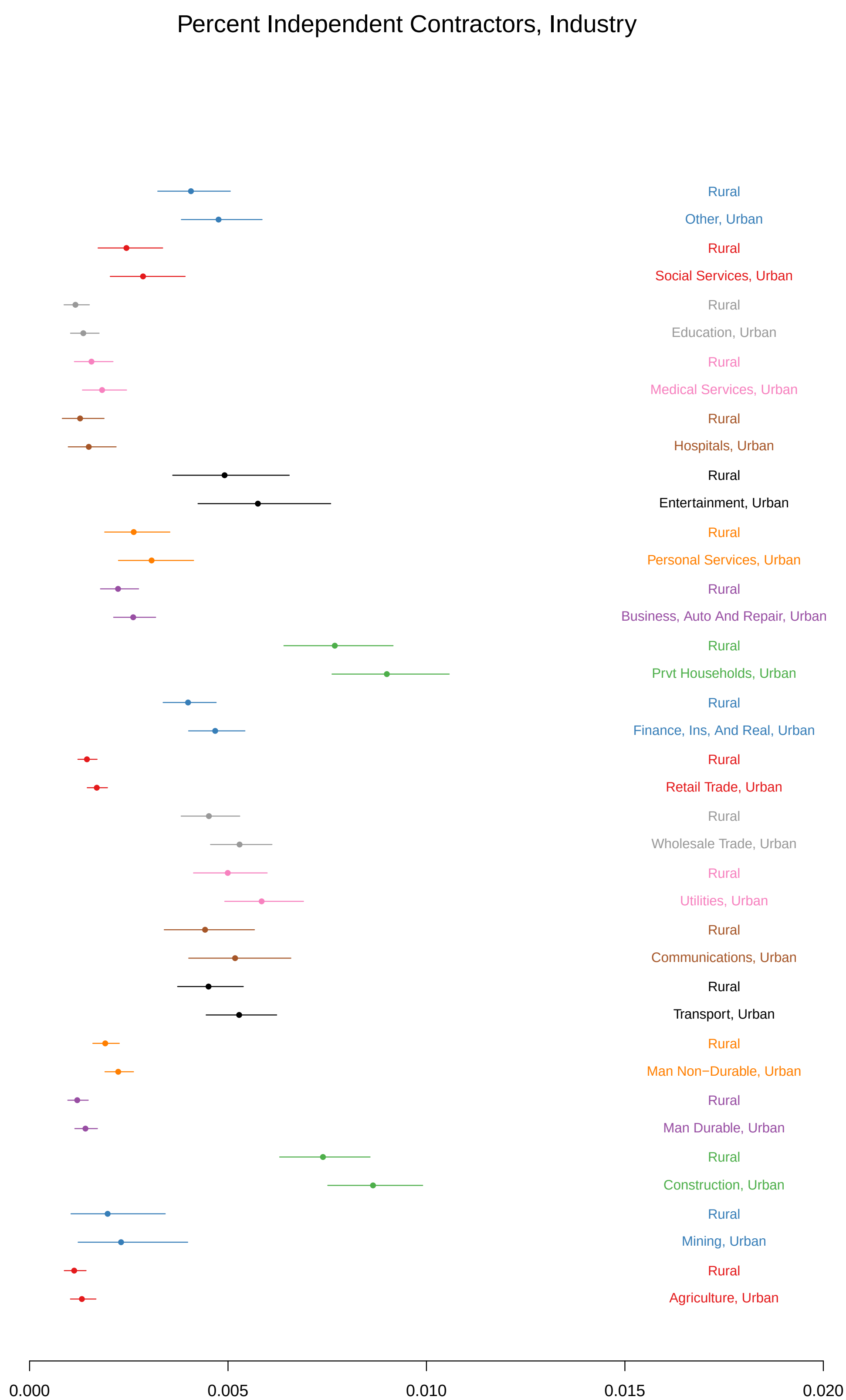

Percent Independent Contractors, Industry
Rural
Other, Urban
Rural
Social Services, Urban
Rural
Education, Urban
Rural
Medical Services, Urban
Rural
Hospitals, Urban
Rural
Entertainment, Urban
Rural
Personal Services, Urban
Rural
Business, Auto And Repair, Urban
Rural
Prvt Households, Urban
Rural
Finance, Ins, And Real, Urban
Rural
Retail Trade, Urban
Rural
Wholesale Trade, Urban
Rural
Utilities, Urban
Rural
Communications, Urban
Rural
Transport, Urban
Rural
Man Non−Durable, Urban
Rural
Man Durable, Urban
Rural
Construction, Urban
Rural
Mining, Urban
Rural
Agriculture, Urban
0.000
0.005
0.010
0.015
0.020

Figure 8

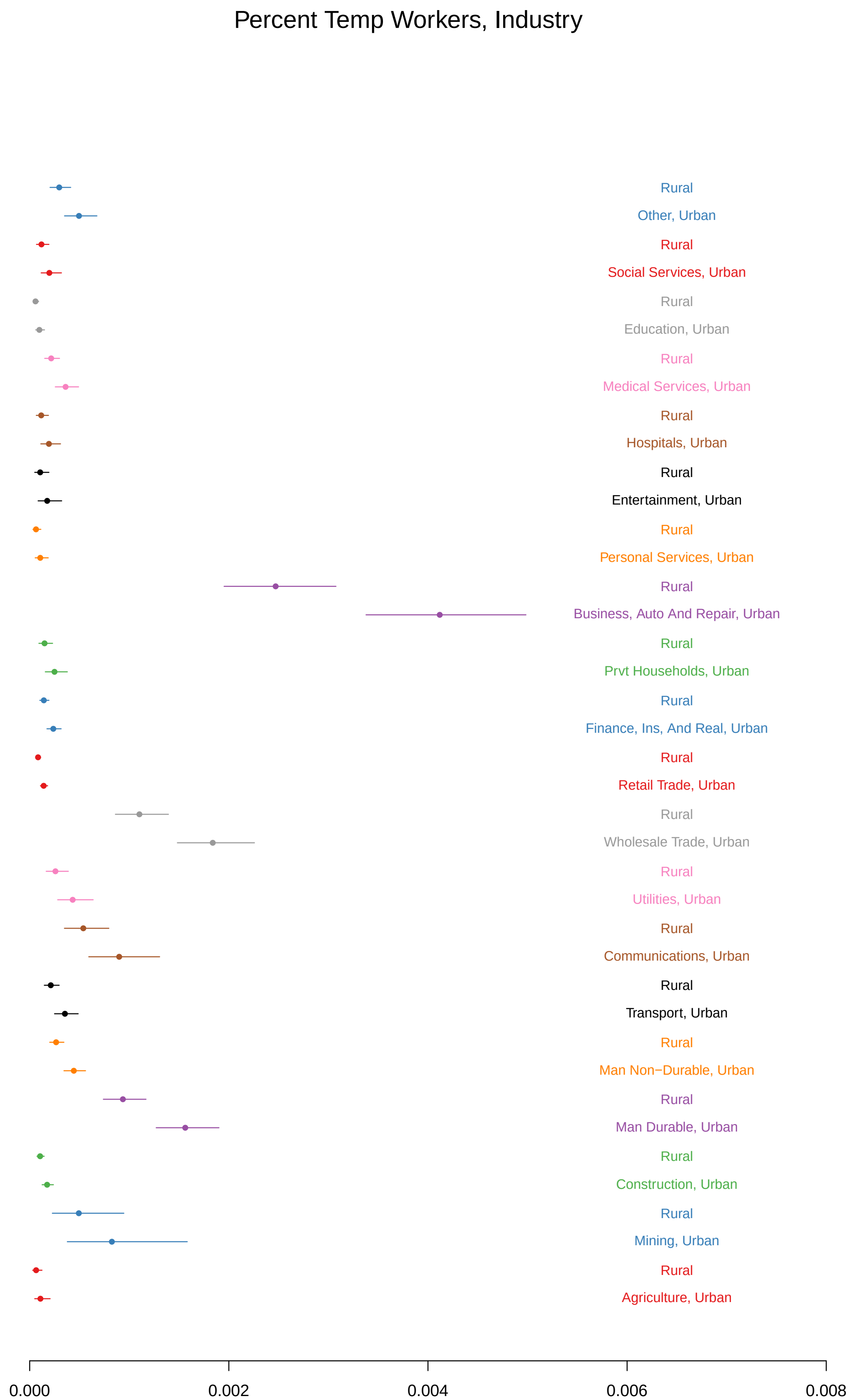

Percent Temp Workers, Industry
Rural
Other, Urban
Rural
Social Services, Urban
Rural
Education, Urban
Rural
Medical Services, Urban
Rural
Hospitals, Urban
Rural
Entertainment, Urban
Rural
Personal Services, Urban
Rural
Business, Auto And Repair, Urban
Rural
Prvt Households, Urban
Rural
Finance, Ins, And Real, Urban
Rural
Retail Trade, Urban
Rural
Wholesale Trade, Urban
Rural
Utilities, Urban
Rural
Communications, Urban
Rural
Transport, Urban
Rural
Man Non−Durable, Urban
Rural
Man Durable, Urban
Rural
Construction, Urban
Rural
Mining, Urban
Rural
Agriculture, Urban
0.000
0.002
0.004
0.006
0.008

Figure 9

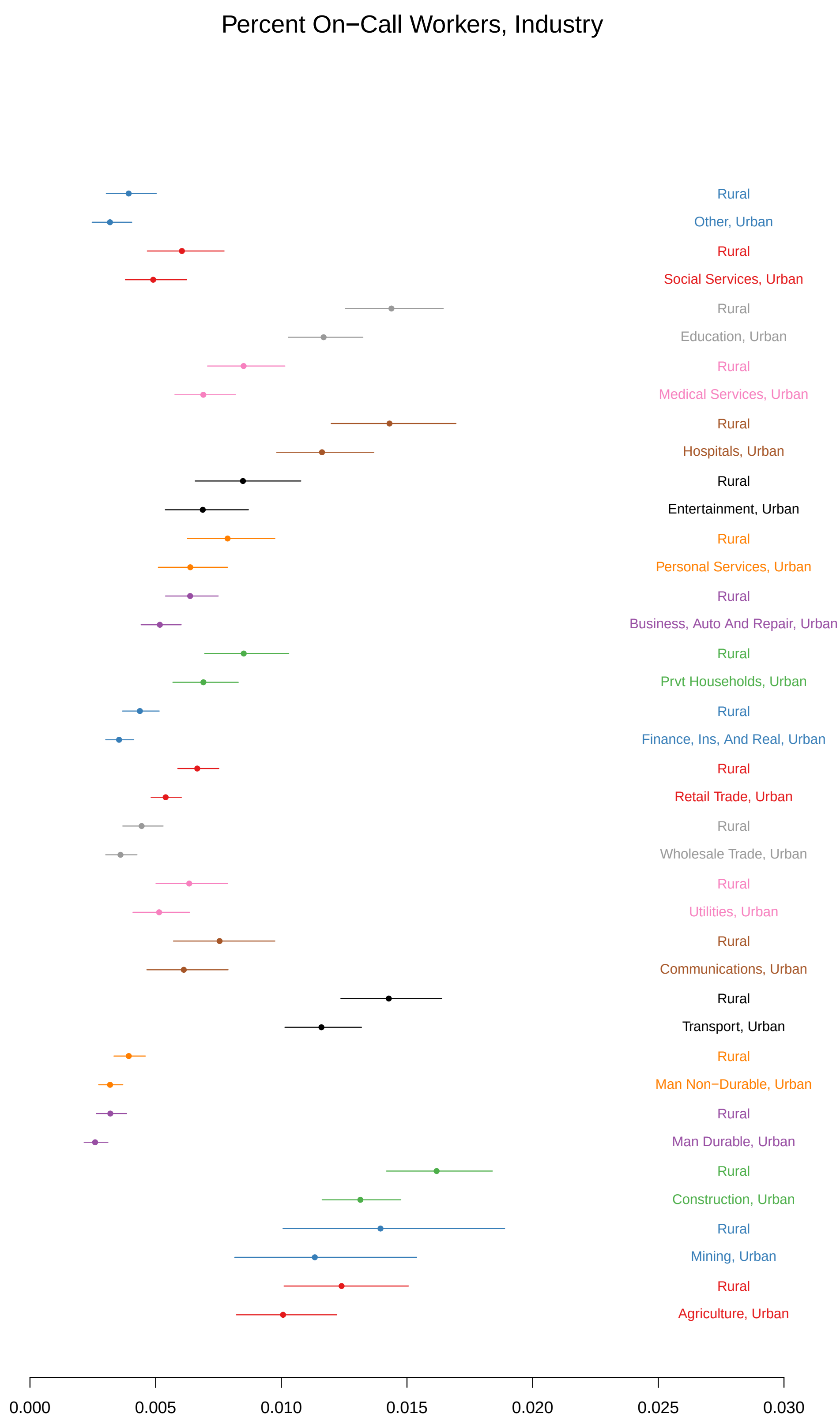

Percent On−Call Workers, Industry
Rural
Other, Urban
Rural
Social Services, Urban
Rural
Education, Urban
Rural
Medical Services, Urban
Rural
Hospitals, Urban
Rural
Entertainment, Urban
Rural
Personal Services, Urban
Rural
Business, Auto And Repair, Urban
Rural
Prvt Households, Urban
Rural
Finance, Ins, And Real, Urban
Rural
Retail Trade, Urban
Rural
Wholesale Trade, Urban
Rural
Utilities, Urban
Rural
Communications, Urban
Rural
Transport, Urban
Rural
Man Non−Durable, Urban
Rural
Man Durable, Urban
Rural
Construction, Urban
Rural
Mining, Urban
Rural
Agriculture, Urban
0.000
0.005
0.010
0.015
0.020
0.025
0.030

Figure 10

Percent Contract Company Workers, Industry

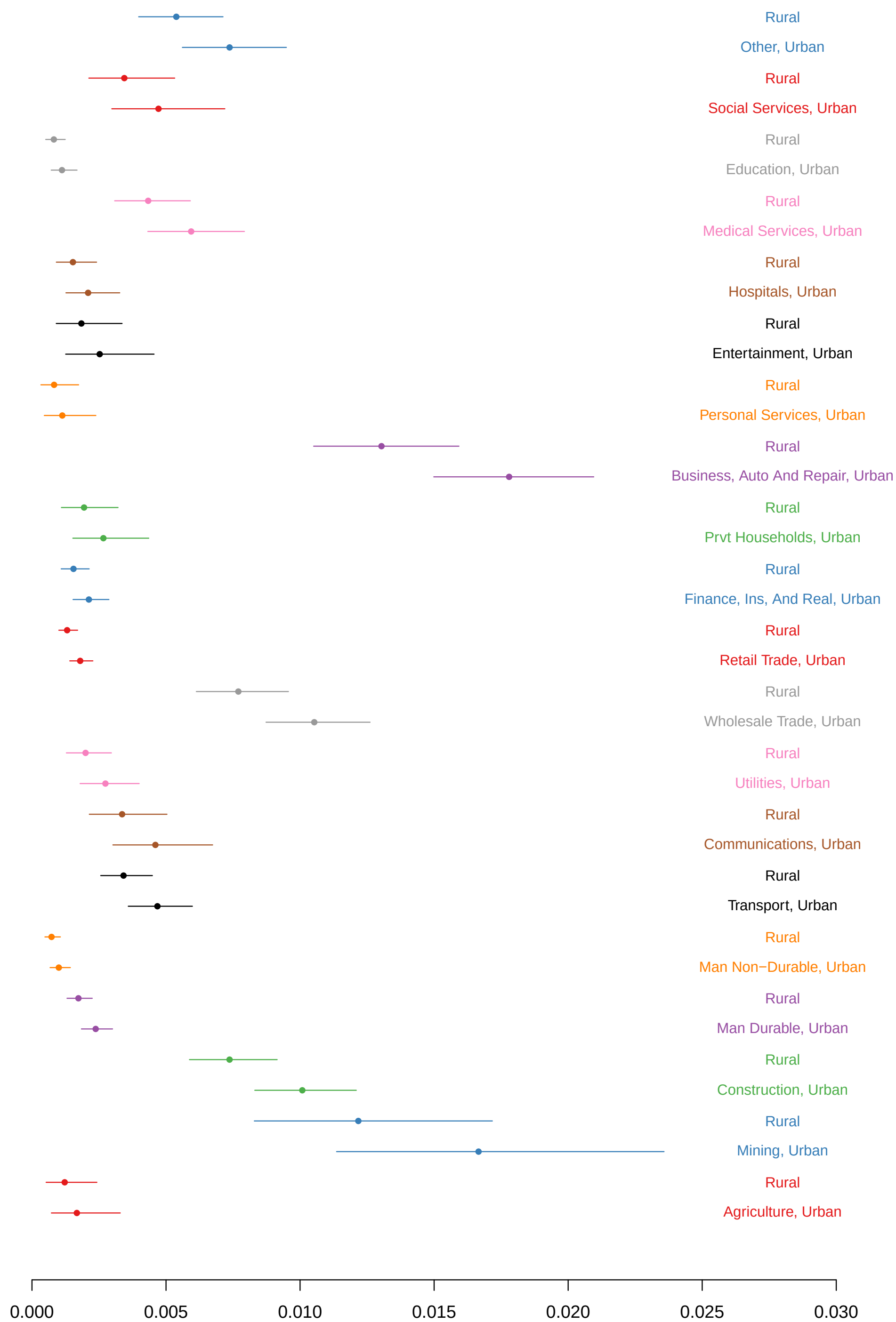
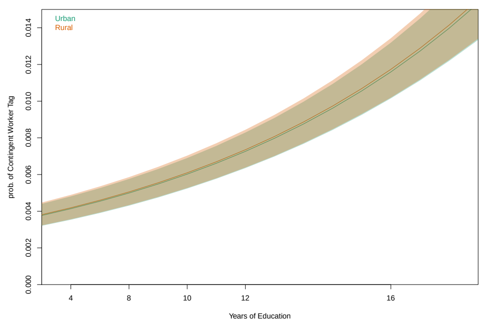
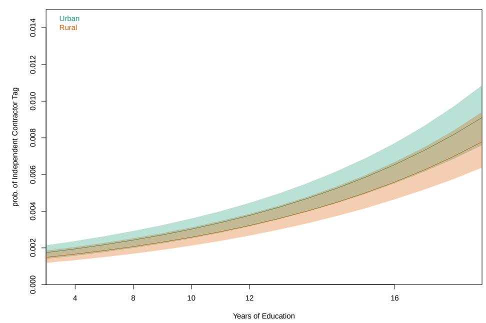


Figure 11

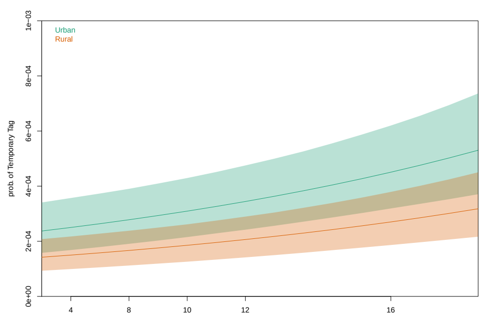
Worker Classification and Education



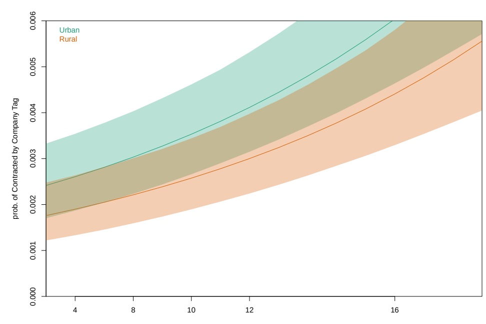
(a) Contingent Workers



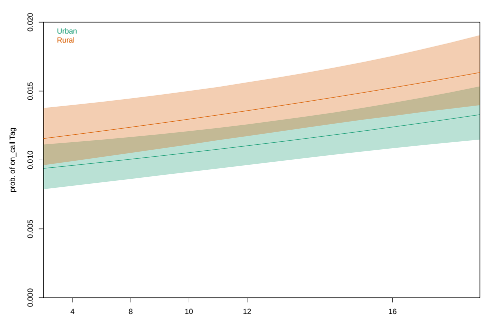
(b) Independent Contractors



(c) Temporary Help Agency Worker



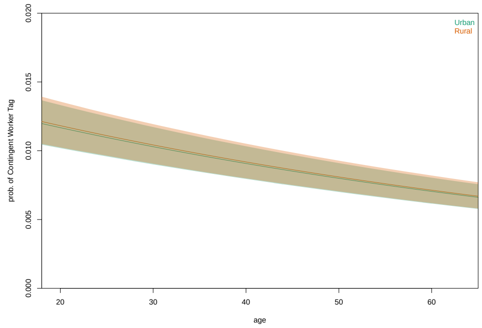
(d) Workers Provided by Contract Firms



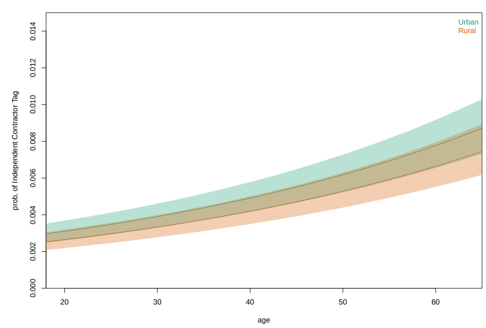
(e) On-Call Workers

Figure 12

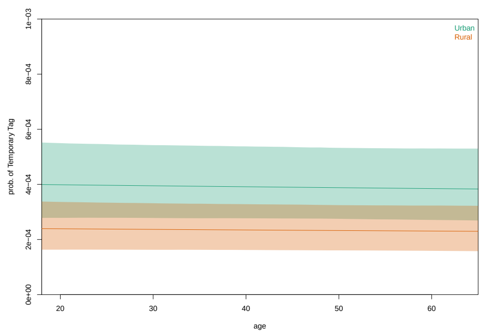
Worker Classification and Age



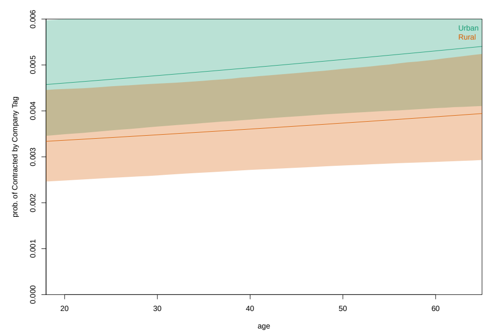
(a) Contingent Workers



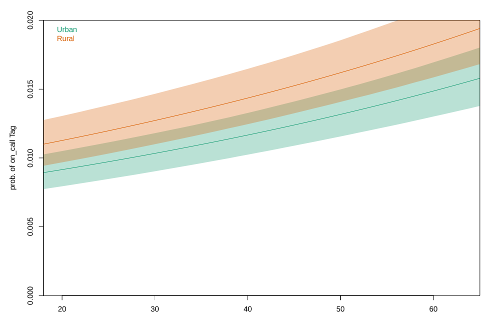
(b) Independent Contractors



(c) Temporary Help Agency Worker



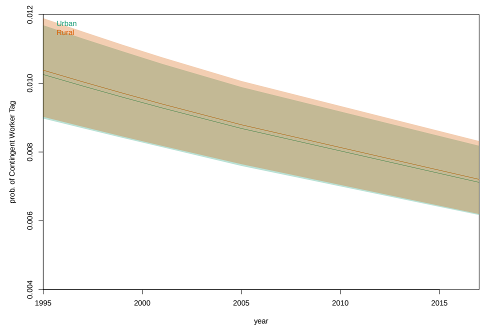
(d) Workers Provided by Contract Firms



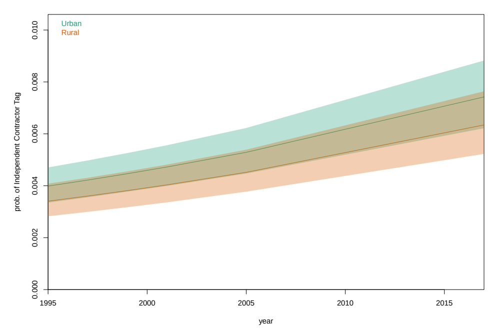
(e) On-Call Workers

Figure 13

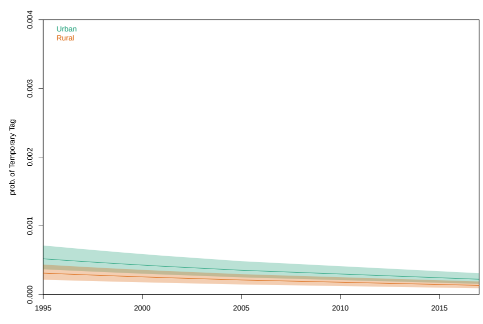
Worker Classification and Year



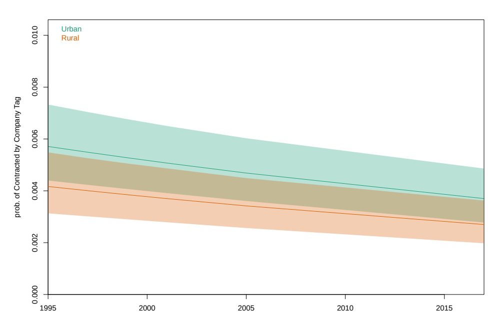
(a) Contingent Workers



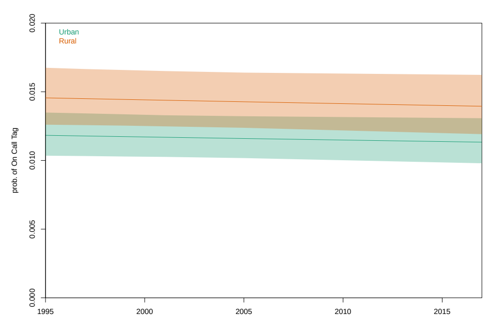
(b) Independent Contractors



(c) Temporary Help Agency Worker



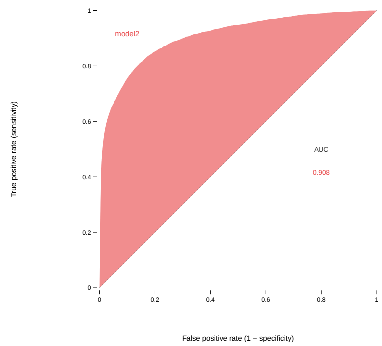
(d) Workers Provided by Contract Firms



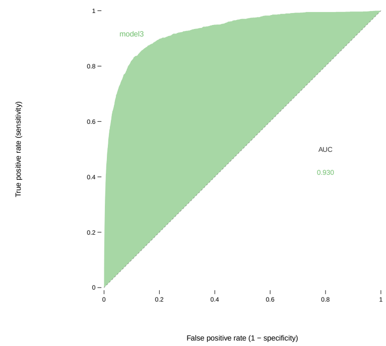
(e) On-Call Workers

Figure 14

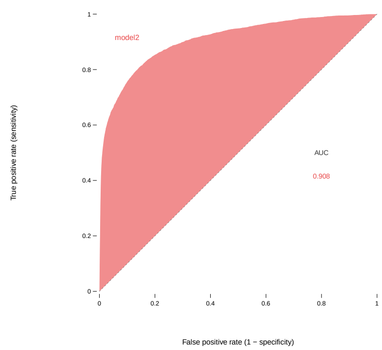
ROC Plots of Each Model



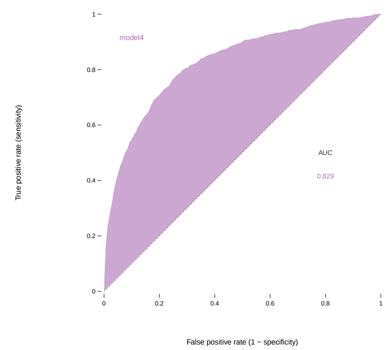
(a) Contingent Workers



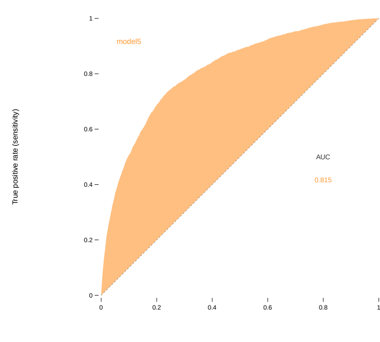
(b) Independent Contractors



(c) Temporary Help Agency Worker



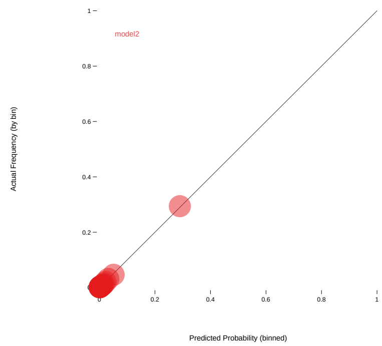
(d) Workers Provided by Contract Firms



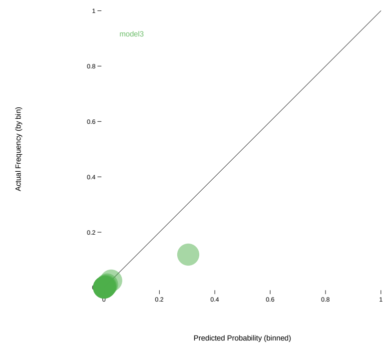
(e) On-Call Workers

Figure 15

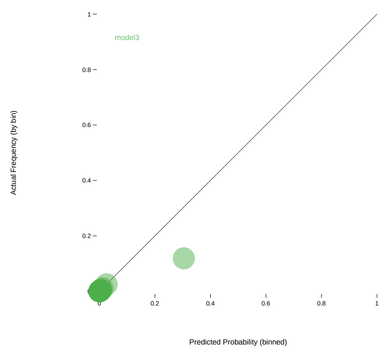
Actual v. Predicted Plots of Each Model



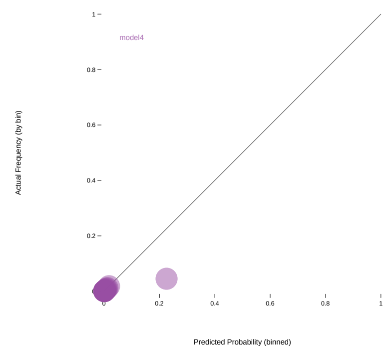
(a) Contingent Workers



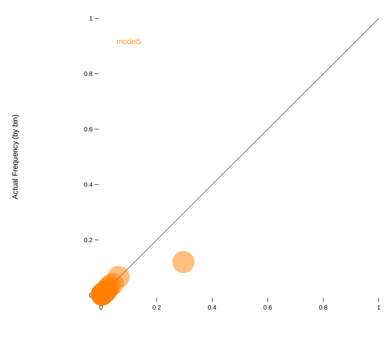
(b) Independent Contractors



(c) Temporary Help Agency Worker



(d) Workers Provided by Contract Firms



(e) On-Call Workers

Figure 16

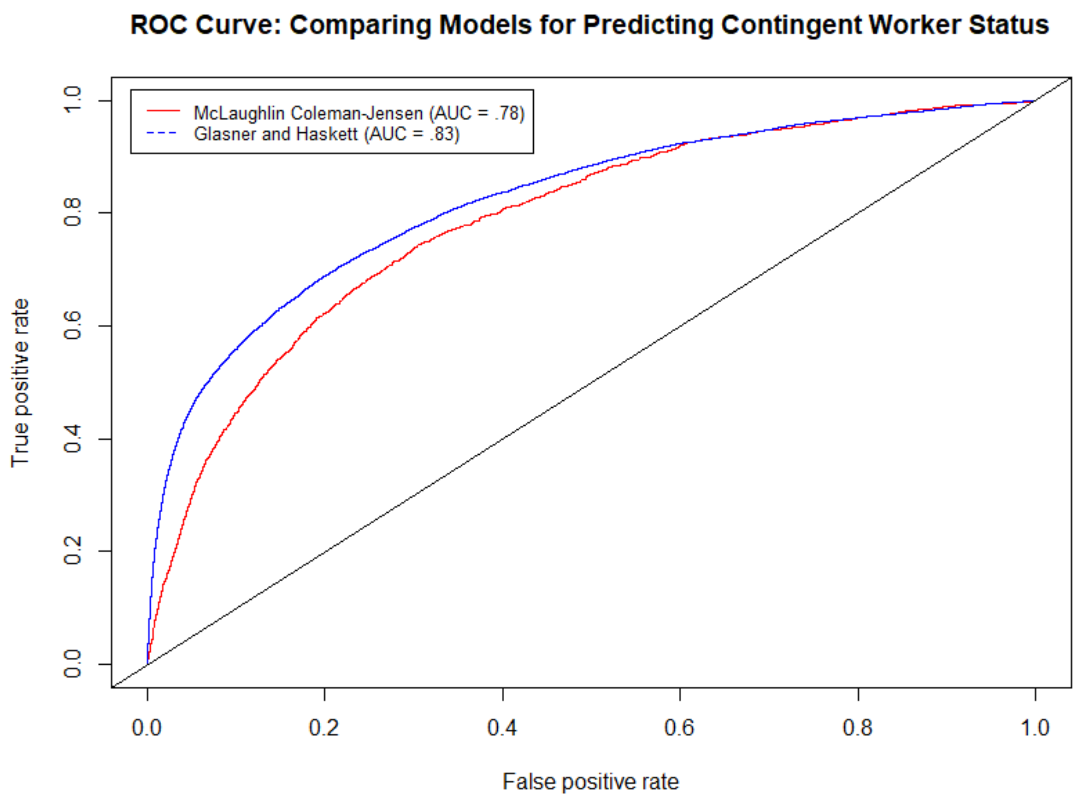

ROC Curve: Comparing Models for Predicting Contingent Worker Status
McLaughlin Coleman-Jensen (AUC = .78)
Glasner and Haskett (AUC = .83)
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0

Figure 17