Measuring Overtime Exemption Status: A Task-Based Approach*

Kevin Rinz

Federal Reserve Bank of Cleveland

July 7, 2026

Abstract

This paper introduces new measures of the overtime exemption status of individual tasks measured by O*NET. Task-based measures reveal that about 60 percent of salaried workers are in occupations in which either all or no O*NET tasks are exempt. While workers with higher earnings tend to be employed in occupations in which a larger share of tasks are exempt, there is substantial variation in exempt task shares across occupations at all levels of earnings. The task content of job ads shows a similar pattern. Incorporating task-based exemption measures into extensions of prior work reveals that workers in high-exemption occupations were more likely to transition out of salaried jobs affected by changes to state overtime rules, and managerial jobs just above the federal salary level test threshold have exempt task content similar to those just below it.

Keywords: Fair Labor Standards Act, overtime, exemption, salary, O*NET, tasks, LLM
JEL classification: J38, J88

*Any views, opinions, and conclusions expressed herein are those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System. I thank Lisa Barrow for helpful suggestions and Kevin Jacobson and Carol Moseley for help with cross-checking LLM classifications of O*NET tasks. The analysis underlying this paper was conducted with the help of artifical intelligence, specifically Claude Sonnet 4.5, Sonnet 4.6, and Opus 4.6.

1 Introduction

Under the Fair Labor Standards Act (FLSA) of 1938, covered workers are required to be paid a premium of at least 150 percent of their regular rate of pay for hours worked in excess of 40 per week. Under the statute, whether a worker is covered is based on the content of their job. Workers employed in a "bona fide executive, administrative, or professional capacity" are exempt from the overtime pay requirement, with the details of these "EAP" or "white-collar" exemptions left to the Department of Labor (DOL) to establish and operationalize via regulation.[1]

In implementing these exemptions, DOL has historically applied three tests to determine a worker's status: a salary basis test, a salary level test, and a duties test. The salary basis and salary tests are straightforward: to be exempt, a worker must be paid on a salary basis (i.e., paid a consistent amount that does not vary based on the quantity or quality of work performed) and the salary must be at least a certain amount per week (currently $684). The duties test is more complex. DOL provides high-level guidance on the types of duties that qualify for each exemption (see Table 1), but exemption determinations for individual workers are made on a case-by-case basis. This system creates uncertainty for both employers and workers, who could have different views about things like which duties are primary or how much discretion workers can exercise.

The system also creates challenges for researchers, since readily available measures of job characteristics like occupation or job title are not dispositive for exemption status, and no comprehensive, nationally representative data source records the detailed job duties needed to determine exemption status for individual workers. Researchers therefore observe neither which workers perform which duties nor which duties constitute exempt work.

In this paper, I address the second of these two challenges by using a large language

[1] The FLSA also exempts many other, smaller categories of workers from overtime coverage, (e.g., outside salespeople, fishermen, employees of small farms, employees of small newspapers, and various others). These exemptions are explicitly delimited in the statute and are much more limited in scope, and they are not the focus of this paper.

model (LLM) to construct a new measure of the exemption status of every task recorded in the O*NET database since 2008. I then use data on the relevance, importance, and frequency of performance of each task to construct occupation-level measures of exemption status. Descriptive analysis of these measures produces several important insights.

First, 60 percent of salaried workers are employed in occupations within which either all or none of the tasks measured by O*NET are exempt, making the precise details of the duties test relevant to only a relatively small share of all workers. Second, while workers with higher earnings tend to be employed in occupations in which a larger share of tasks are exempt, there is substantial variation in the exempt task share across occupations at all levels of the earnings distribution. This result is robust to assuming high degrees of within-occupation correlation between earnings and performance of exempt tasks. The task content of job ads shows a similar pattern. Finally, these exemption measures suggest that, under the current duties test, the share of workers who would be classified as exempt based on their duties but are made non-exempt based on having a salary below the salary level test threshold is small.

The task-based exemption measurement infrastructure developed in this paper will enable researchers and policymakers to extend analyses of overtime regulations beyond considering the effects of changes in salary thresholds. While a few studies consider the introduction or more general expansions of coverage under the FLSA or similar state rules (Costa, 2000; Hamermesh and Trejo, 2000; Johnson, 2003; Trejo, 2003), much of the existing research on overtime rules (Brown and Hamermesh, 2019; Goff, 2024; Quach, 2024, 2025) reflects the fact that changes to overtime policy have consisted primarily of changes to the salary level test. This fact may itself be a consequence of the difficulty of measuring workers' duties, and attempts to distinguish exempt from non-exempt workers without better measurement of duties can be coarse (e.g., Trejo, 1991). Cohen et al. (2023) consider the degree to which employers would prefer to avoid dealing with the duties test, finding an increased incidence of "fake-sounding" managerial job titles in job ads with pay just above the salary level test threshold, but they do not observe the content of these jobs or their exemption status. The measures developed in this paper could allow for additional, nuanced analysis of past policy changes and improve our understanding of the potential effects of future changes, potentially including changes to the duties test.

As a starting point, I revisit two recent analyses and extend them using task-based exemption measures. First, using the Current Population Survey and an approach that follows Quach (2024), I reproduce that paper's result that increases in state salary level test thresholds move workers out of salaried jobs in the affected salary range, and I find that this effect is somewhat larger for workers in occupations with high exempt task shares. In the spirit of Cohen et al. (2023), I also examine job ads with O*NET tasks flagged and exemption information attached, and I find little change in the prevalence of managerial job titles or the exempt content of managerial jobs around the federal salary level test threshold, conditional on salary, education and experience requirements, and employer fixed effects.

The rest of this paper is organized as follows. Section 2 provides background on overtime exemptions and recent regulatory history. Section 3 describes construction of the task-based exemption measures. Section 4 uses the task-based exemption measures to describe the relationship between earnings and exemption status, and to extend prior causal analyses of overtime rules. Section 5 concludes.

2 Institutional Background

Overtime protections, alongside the minimum wage and rules around child labor, are a major component of the FLSA. Workers subject to those protections must be paid 150 percent of their usual wage for hours worked beyond 40 per week. The FLSA defined several exemptions to the overtime protections, which DOL implements through regulations.

DOL's overtime regulations establish three tests to determine whether a worker must be paid the wage premium for hours over 40: the salary basis test, the salary level test, and the duties test. A worker who passes all three tests is classified as exempt and is not required to be paid the wage premium.

A worker passes the salary basis test by being paid a fixed salary that does not vary with the quantity or quality of work performed. A worker passes the salary level test by being paid a salary that exceeds some threshold, currently $684 per week. A worker passes the duties test by having job duties that are primarily executive, administrative, or professional in nature, with those terms being defined by regulation.

2.1 The White-Collar Exemptions

The executive, administrative, and professional (EAP) exemptions, sometimes referred to collectively as the white-collar exemptions, form the most significant category of exemptions from overtime coverage.[2] The executive, administrative, and professional exemptions each apply based on the nature of a worker's primary duty, where the primary duty is the "principal, main, major, or most important" duty the worker performs.[3]

The statutory text related to the EAP exemptions is very limited. In order to qualify, the statute says that a worker must be employed "in a bona fide executive, administrative, or professional capacity."[4] Implementation of this requirement is left to DOL to carry out via regulation. Table 1 summarizes the current regulatory implementation of each of the EAP exemptions.

2.2 Brief History of Recent Overtime Regulations

In 2004, the George W. Bush administration finalized the first broad, lasting change to overtime regulations since 1975. The 2004 rule consolidated the essentially defunct "long" duties test, which nominally set a higher bar for exemption among especially low-paid workers, with the "short" test, which was somewhat less strignent on its face and applied to workers earn-

[2]Separate exemptions exist for workers in outside sales and some computer-related occupations, but these are not subject to the same duties-measurement issues as the EAP exemptions, and they are beyond the scope of this paper.

[3]See 29 CFR 451.700(a).

[4]See 29 USC 213(a)(1).

ings slightly more, into a new standard test and set the salary level test threshold at $455 per week, an increase from the $250 per week threshold that had been associated with the short test.[5] The new threshold aligned with the 20th percentile of weekly earnings for full-time salaried workers in the lowest-wage Census region, which was, at the time, the South. In its 2004 final rule, DOL described the move to the standard duties test as resulting in only "de minimis differences" from the short test (Wage and Hour Division, US Department of Labor, 2004).

Since then, each subsequent administration has proposed further changes, all primarily focused on modifying the salary level test threshold. In May 2016, the Obama administration finalized a rule that would have raised the salary level test threshold to $913 per week, aligning with the 40th percentile of earnings for full-time salaried workers in the lowest-wage Census region (again the South). In November 2016, shortly before the rule was set to take effect, a federal judge enjoined DOL from implementing or enforcing it; subsequent legal proceedings invalidated the rule without it ever taking effect.

In September 2019, the Trump administration issued a final rule that raised the salary level test from $455, where it had remained as a result of the invalidation of the Obama administration's rule, to $684 per week, again applying the 20th percentile peg used in the 2004 rule. This rule did not face a meaningful legal challenge.[6]

In April 2024, the Biden administration finalized a rule that would raise the salary level test threshold to $844 starting July 1, 2024, raise it further to $1,128 on January 1, 2025, and update it automatically every three years thereafter (Wage and Hour Division, US Department of Labor, 2024). The July increase took effect, but the rule was blocked by a federal judge in November 2024. At that point, the salary level test threshold reverted to the $684 per week level set by the 2019 rule.

[5]The "long" duties test applied to executive and administrative workers earning less than $155/week and professional workers earning less than $170/week. These thresholds were below the weekly earnings of a full-time worker earning the federal minimum wage in 2004.

[6]The 2019 rule was challenged by the proprietor of several Texas Dairy Queens (Pacific Legal Foundation, 2024). In contrast, the 2016 rule was challenged by 21 states and the US Chamber of Commerce (Scheiber, 2016).

The judge's opinion blocking the 2024 rule concluded that the salary level threshold it attempted to set would increase the rate at which workers with exempt duties were classified as non-exempt on the basis of their salary to such an extent that it would amount to a replacement of the duties test with a salary-only test, and that such a change exceeded DOL's statutory authority. If this reasoning is applied to future changes to overtime regulations, it could constrain future changes to the salary level test unless such changes are accompanied by changes to the duties test.

3 Constructing Task-Based Exemption Measures

Overtime exemption determinations are made based on individual workers' duties and the particular context of their jobs. Those circumstances are very difficult for researchers to observe, but information about the tasks that make up jobs is more readily available from O*NET. Assessing the exemption status of tasks creates building blocks for a more nuanced study of overtime rules and the FLSA more broadly. I perform this assessment with the help of a large language model, consistent with a growing literature using such tools to classify or categorize data by processing textual information (for example, Eloundou et al., 2024; Kim et al., 2024; Bartik et al., 2025; Labaschin et al., 2025; Massenkoff and McCrory, 2026). Evaluations suggest that the accuracy of LLM classifiers is comparable to human classifiers (Gilardi et al., 2023; Törnberg, 2023; Kim et al., 2024; Le Mens and Gallego, 2025; Bartik et al., 2025; Heseltine and Clemm von Hohenberg, 2024).

3.1 The O*NET Task Database

O*NET is a comprehensive database of worker and job characteristics sponsored by DOL's Employment and Training Administration (ETA). Data are collected for nearly 1,000 occupations via surveys of workers and experts. In addition to their research uses, the data have practical applications in workforce development and feed into multiple online tools intended to help workers identify jobs or career paths in which they might be interested.

This project is based on information from O*NET's task database. Tasks are narrowly defined activities associated with particular occupations. For example, there are 28 tasks associated with the occupation Food Service Managers in version 30.2 of the database (current as of this paper), including

- Test cooked food by tasting and smelling it to ensure palatability and flavor conformity
- Investigate and resolve complaints regarding food quality, service, or accommodations
- Schedule and receive food and beverage deliveries, checking delivery contents to verify product quality and quantity
- Monitor food preparation methods, portion sizes, and garnishing and presentation of food to ensure that food is prepared and presented in an acceptable manner.

For each task, O*NET provides measures of its relevance and importance to its occupation, as well as measures of how frequently it is performed. A task's relevance measure is the share of survey respondents who report that the task is relevant to the performance of the occupation with which it is associated. A task's importance measure is the average assessment, on a scale from 1 to 5, of its importance to the occupation, provided only by respondents who reported that the task was relevant to the occupation. Frequency information for each task comes in several measures that give the shares of respondents reporting that a task is performed at various frequencies ranging from once a year or less often to hourly or more often.

3.2 Classification Methodology

All tasks in the O*NET database since 2008 have been classified by Claude Sonnet 4.6 as exempt or non-exempt. Classification was completed during March 2026 via the Claude Code command line interface and was based on the task statement, the associated occupation, and a set of background documents related to the FLSA, EAP exemptions, overtime regulations, and DOL's implementation practices.[7] The core task the model was asked to complete was posed as follows:

> You will be presented with a series of occupation-task pairs. For each pair, you should answer the following question: Suppose a full-time salaried employee working as [occupation] performs the following task frequently or as a primary part of their job: [Insert O*NET task description here.] Does this task suggest that the employee is more likely to be classified as exempt or non-exempt under the FLSA overtime rules, assuming all other factors are held constant and the worker's overtime exemption status is not already determined by some other factor?

The model was asked to return three pieces of information for each task: a binary classification of the task as exempt or non-exempt; the specific exemption that applied, if any (e.g. executive, creative professional, computer employee, etc.); and a brief explanation of the reasoning behind the classification. Overall, the model classified 23,854 tasks in this way.[8]

The LLM's classifications are broadly simialr to those produced by human coders. Two human coders were given the same instructions and background documents as the LLM and asked to classify a 1 percent sample of tasks.[9] One coder's exempt/non-exempt classifications aligned with the LLM's on 84.6 percent of tasks, while the other's aligned with the LLM on 87.2 percent of tasks. Interestingly, each human coder agreed with the LLM more often than they agreed with each other, with the two human coders agreeing on 80.3 percent of tasks. There was consensus among the two human coders and the LLM on 76.1 percent of tasks.

[7]See Appendix A for a full list of documents and more detailed instructions.

[8]The dataset of classified tasks can be downloaded from https://kevinrinz.github.io/overtime.html. Several interactive tools for exploring the data are also available there.

[9]The human coders were research analysts at the Federal Reserve Bank of Cleveland.

3.3 Occupation-Level Exemption Measures

I combine task-level exemption classifications and relevance, importance, and frequency information to construct several occupation-level measures of exemption status based on the exemption status of tasks. These measures are continuous, reflecting the share of tasks within an occupation that are classified as exempt. While a simple average of the exemption status of component tasks is straightforward and universally feasible, data on the relevance, importance, or frequency of performance of each task can be used as weights that focus on different ways of thinking about the centrality of a task to a worker's job. Ultimately, these approaches produce similar results on average and are highly correlated with each other.[10]

Figure 1 shows histograms of the share of tasks classified as exempt at the occupation level for select years. Panel (a) gives all occupations equal weight. A large majority of occupations have either 0 percent or 100 percent of tasks classified as exempt in all years. Having 0 percent of tasks classified as exempt is both the modal and the median outcome, though the share of occupations without any exempt tasks has declined from nearly 60 percent in 2008 to just over 50 percent in 2025. The share of occupations with all tasks classified as exempt has been more stable over this period, rising from just over 14 percent in 2008 to nearly 17 percent in 2025. Panel (b), which weights occupations by employment, shows that about 50 percent of workers in 2025 were employed in occupations with no exempt tasks, while about 10 percent of workers are employed in occupations with all tasks classified as exempt. This leaves about 25 million workers (40 percent of the 63.5 million salaried workers) employed in occupations with a mix of exempt and non-exempt tasks. The precise details of the duties test are therefore only potentially relevant to about 18 percent of all workers.[11]

Given the lack of data available on workers' duties and exemption status, it is difficult

[10]Pairwise correlations between the measures produced all exceed 0.99. Underlying measures are also available at https://kevinrinz.github.io/overtime.html.

[11]CPS ORG data show 143.5 million workers employed in the average month in 2025, making the 25.4 million workers in mixed occupations about 18 percent of all workers.

to assess the quality of these measures. However, I can compare them to the exemption measures used in regulatory impact analyses of recent overtime rule changes. These measures place each occupation into one of five categories corresponding to the probability that a worker in that occupation is exempt (0 percent, 0-10 percent, 10-50 percent, 50-90 percent, and 90-100 percent). The codes were based on the expert judgment of staff in DOL's Wage and Hour Division in 1998 and have been used in all subsequent analyses of overtime rule changes.

Exemption shares implied by the task-based measures are generally consistent with the DOL probability codes. Table 2 reports the mean share of tasks classified as exempt for each DOL probability code, as well as the share of workers employed in occupations where more than 50 percent of tasks are classified as exempt. Both task and worker exemption shares are lowest within the DOL codes associated with the lowest probabilities of exemption and highest within the DOL codes associated with the highest probabilities of exemption. However, the DOL codes may somewhat understate exemption prevalence within occupations that are less likely to be exempt. Within occupations that DOL classifies as 0 percent exempt, around 4-5 percent of tasks are exempt and about 5 percent of workers are employed in occupations where more than 50 percent of tasks are exempt; in the 0-10 percent category, these figures are just over 10 percent of tasks and around 13 percent of workers. In the 10-50 percent exempt group, the shares are about 35-40 percent of tasks and around 45 percent of workers.[12]

Figure 2 shows the distribution of the share of tasks classified as exempt at the occupation level within each DOL probability code for 2008 and 2025. The distributions are generally

[12]There are no precise quantitative values associated with the requirement that workers be engaged in certain activities as their primary duties, but according to the section defining primary duty in the Code of Federal Regulations, workers who spend more than 50 percent of their time performing exempt work will generally satisfy the primary duty requirement (see 29 CFR 541.700(b)). Therefore, I use 50 percent exempt duties as the threshold for classifying workers as exempt or non-exempt based on the task-based measures. Appendix Table C1 reports tabulations using 75 percent and 90 percent thresholds, which are also arbitrary and would seem to correspond to substantially more stringent qualitative characterizations than "primary." These formulations also show a greater degree of exemption in the higher-exemption DOL categories, but they also show much lower levels of exemption in all categories, to a degree that does not correspond well to the values implied by the DOL codes.

consistent with the DOL codes, with higher shares of exempt tasks in higher-exemption DOL categories. However, there is substantial variation within each DOL category, and meaningful overlap between the distributions of exempt task shares across DOL categories. This is true in both years. The most notable shift between 2008 and 2025 is the large increase in the upper percentiles of the distribution of exempt task shares within the 0-10 percent category and more modest but still notable decreases in the lower percentiles of the distribution of exempt task shares within the 90-100 percent category.

4 Insights from the Task-Based Exemption Measure

4.1 Contextualizing the Salary Level Test Threshold

The text of the FLSA delineates exemptions from overtime coverage based on workers' duties. DOL has long used the salary level test as a practical tool to simplify implementation of exemption determinations: evaluating the details of every worker's duties would be very time consuming and costly for both employers and agency staff charged with enforcing overtime rules, while making all workers with earnings below some threshold non-exempt simplifies matters greatly. This approach balances the benefits of that simplification against the costs of classification errors that lead some workers with exempt duties to be treated as non-exempt by virtue of their salaries. That balance, however, is difficult to assess without more information about which workers are performing exempt work and how much they earn. In this section, I use task-based exemption measures to examine that relationship, with a particular focus on how it interacts with the salary level test threshold.

4.1.1 Earnings by Exemption Status

Given the close connection between the distribution of earnings among salaried workers and the salary level test threshold, I first consider how earnings differ across groups defined by occupation-level task-based exemption status. Figure 3a shows the empirical cumulative distribution function of weekly earnings in 2025 for all salaried workers, workers in occupations who perform a mix of exempt and non-exempt tasks, and workers in occupations who perform only exempt or only non-exempt tasks. Earnings are notably lower in fully non-exempt occupations. The current salary level test threshold of $684 per week is at about the 23rd percentile of earnings for workers in fully non-exempt occupations, while it is just above the 6th percentile for fully exempt and mixed occupations. The differences are similarly pronounced for full-time salaried workers (Figure 3b) and for full-time salaried workers in the South (Figure 3c), the group actually used to set the salary level threshold. The CDFs for fully exempt and mixed occupations are very similar to each other, especially below $1,000 of weekly earnings.

4.1.2 Exemption Status by Earnings

Among salaried workers, the share of tasks classified as exempt at the occupation level is increasing in weekly earnings. The rate of increase jumps when earnings cross the $684 threshold: below it, the average worker is in an occupation with about 30 percent exempt tasks; above it, this share exceeds 50 percent by about $1,000 per week and stabilizes north of 70 percent around $2,900 per week. Figure 4a depicts this trajectory.

This pattern of a rising exempt task share above the salary level test threshold has been fairly consistent over time, even as the threshold has changed. Before the salary threshold was set at its current level in 2019, the increase in the share of tasks classified as exempt began at a lower level of earnings that aligned more closely with the prior salary level threshold ($455), as shown in Figure 4b. The increase was also more pronounced in prior years, with the share of tasks classified as exempt typically beginning in line with or somewhat above the level seen in 2025 below the threshold and then rising to higher levels at higher earnings. The consistency with which this measure changes trajectory around the salary level test threshold suggests that the threshold does have some influence on the nature of jobs at nearby earnings levels. This could point to bunching of jobs with greater shares of exempt tasks above the salary level test threshold, though the CPS sample is too small to test this directly.

4.1.3 Individual-level Measures of Exemption Status

Though the exemption measures discussed so far are generated at the task level, applications to workers have relied on occupation-level measures. Working at the occupation level is potentially limiting with respect to analyses of the joint distribution of earnings and exemption status, since there is substantial within-occupation variation in both, as well as substantial overlap in the distribution of earnings across occupations, including across occupations that perform exempt work with dramatically different regularity. Without additional structure, working with occupation-level measures implicitly assumes no within-occupation correlation between earnings and the performance of exempt tasks, which is unlikely to be correct and could lead to a misunderstanding of the relationship between earnings and exemption status across the earnings distribution.

To test the sensitivity of my results to this issue, I use a latent factor model to simulate individual-level task performance under various assumptions about the within-occupation correlation between earnings and the performance of exempt tasks.[13] Since exempt tasks are unlikely to be negatively correlated with earnings, I consider moderate and high degrees of positive correlation. Figure 4c shows that these assumptions influence the shape of the relationship between earnings and exemption status on the margins but do not change the broad pattern. Higher correlations between earnings and performance of exempt tasks reduce the share of tasks that are exempt below the salary level test threshold and increase the share that are exempt at high salaries, but the pattern of rising exempt task share above the salary level test threshold is still evident. MA mre positive correlation between earnings and exempt task performance accentuates rather than alters the patterns revealed by the occupation-level measures.

[13] See Appendix B for details.

I also examine the joint distribution of earnings and exemption status using job ad data from Lightcast. I identify the tasks associated with a 1 percent sample of job ads posted during 2025 by applying the TaskMatch module from the Job Ads Analysis Toolkit, described in Meisenbacher et al. (2025). Again, I find a similar pattern of rising exempt task shares above the salary level test threshold, as shown in Figure 5, though the shares are lower across earnings levels and there is less leveling off in the trajectory at higher earnings. Focusing on full-time jobs with at least 10 O*NET tasks associated with them, the correlation between earnings and exempt task share is about 0.5.[14]

4.1.4 Assessing the Performance of the Salary Level Test

The salary level test is meant to simplify enforcement of a complicated standard, establishing a threshold below which workers can be safely assumed to fail the duties test. Such a test inevitably produces false negatives; that is, it classifies some workers whose duties would lead them to pass the duties test as non-exempt by virtue of their salary. Low false negative rates were an explicit target of early overtime regulations (Wage and Hour Division, US Department of Labor, 2019). In 1958, for example, the Department of Labor targeted a 10 percent false negative rate within various groups of low-wage workers, a standard sometimes referred to as the Kantor test, after a DOL official at the time. The impact of recently proposed changes to the salary level test threshold on false negative rates has played a central role in recent litigation over those changes (Plano Chamber of Commerce, et al. v. United States Department of Labor, et al., 2024).

Moving from DOL's probability code-based approach to identifying workers who pass the duties test to a task-based approach makes it marginally more difficult for recently proposed salary level test thresholds to meet the Kantor test standard, but overall, changes in false negative rates are generally not large in absolute terms.[15] Table 3 shows the share of workers

[14]The job ads analysis also illustrates the flexibility of the task-based exemption measures, which can be applied to any source of information about the task content of a job.

[15]There is nothing economically significant about the salary level test having a 10 percent false negative rate, and the propriety of applying this standard in today's context given changes to the underlying duties

at or below various earnings levels in 2025 who passed several formulations of the duties test that vary the amount of exempt work required to pass and the mechanism for assigning tasks to workers. Under the current salary level test threshold, all formulations show false negative rates that are slightly higher than the rate calculated using the probability-code-based approach, but virtually all false negative rates are below 10 percent, and none exceed 10 percent by more than 0.6 percentage points.

In some cases, switching to a task-based approach is the difference between strictly meeting the Kantor standard or not for certain groups. For the initial $844 threshold proposed in the 2024 rule, both DOL's method and the task-based approach show that the Kantor standard is met for all salaried workers; for workers in the South, DOL's approach shows that the standard is met, while the false negative rate is typically just above 10 percent under the task-based approach. For the $913 threshold proposed in 2016, DOL's approach again shows the Kantor standard is met for all salaried workers, while the task-based approach produces false negative rates just above 10 percent for most formulations.

While changes to the duties test comparable to the possibilities considered here could affect the exemption status of a meaningful number of workers, the stability in the false negative rates across formulations of the duties test for a given threshold is striking.[16] It suggests that modest changes to the duties test would likely have a much smaller effect on the false negative rate/adherence to the Kantor standard than would changes to the salary level test threshold of magnitudes considered recently. This is consistent with the fact that a large majority of workers are in occupations in which either all or no tasks are classified as exempt (Figure 1) and the broad similarity between the earnings CDFs for workers in occupations with a mixture of exempt and non-exempt tasks and workers in occupations with all tasks classified as exempt (Figure 3).

test is disputed. I consider the standard here only because it figured prominently in recent litigation over the 2024 rule.

[16]See Appendix Table C2 for the number of workers exempt under various duties test formulations at various earnings levels.

4.2 Incorporating Task-Base Measures into Causal Analysis

Task-based measures of exemption status could also enhance causal analysis of the effects of overtime rules by enabling consideration of dimensions of heterogeneity or margins of adjustment that were not previously observable. I apply these measures to extensions of two recent papers as a demonstration of their potential value.

4.2.1 Effects of State-Level Salary Level Test Threshold Increases

Some states set their own salary level test thresholds above the level set by DOL. These thresholds are often set as multiples of state minimum wages. Quach (2024) uses data from the payroll processing company ADP to evaluate the effects of changes to state-level salary level test thresholds, finding that they shift workers out of salaried jobs below the new thresholds and into either higher-paying salaried jobs or jobs that pay by the hour. I replicate part of that analysis in spirit using data from the CPS and the same 19 instances of state-level salary level test threshold increases and extend it to consider the possibility of heterogeneous effects by workers' occupation-level task-based exemption status.[17]

Using the longitudinal structure of the CPS, I identify workers who earned salaries between the old and new thresholds in the year before each increase in the salary level test threshold and estimate the effect of the change in the threshold on their labor market status when they are observed again in the CPS 12 months later. Specifically, I estimate the following stacked difference-in-differences model:

$$y_{isvt} = \beta_1 \left(Treat_{st} \times After_{st}\right) + \beta_2 Treat_{st} + \beta_3 After_{st} + \alpha_{vs} + \delta_{vt} + \gamma X_i + \varepsilon_{isvt} \tag{1}$$

where $Treat_{st}$ is equal to one for workers living in states that increased their overtime thresholds (the control group within each event consists of workers in the same salary range

[17] I also extend this analysis to include additional, otherwise qualifying events that took place after the end of the period considered by Quach (2024) and find similar results, which are reported in Appendix Tables C3 and C4.

living in states that never changed overtime rules), $After_{st}$ is equal to one during the year following each event α_{vs} are event-state fixed effects, δ_{vt} are event-time fixed effects, and X_i contains worker-level demographic controls. The coefficient of interest is β_1. I then repeat this analysis for workers who were unemployed during the period before each threshold change to examine effects on the nature of the jobs into which they were subsequently hired. Table 4 reports the results.

Consistent with Quach (2024), raising the salary level test threshold increases the likelihood that salaried workers in the pay range affected by the change will move to another pay status. The probability of being a salaried employee in the affected pay range declines by 7.8 percentage points after increases in the salary level test threshold. This decrease is accompanied by an increase in the probability of being paid by the hour. The increase in hourly jobs is split roughly evenly between those generating weekly earnings at or below the new salary level test threshold and those generating weekly earnings above it.

Among workers who had been unemployed, I find that raising the salary level test threshold reduces the probability that they will subsequently be employed as salaried workers with pay at or below the new threshold by 1.4 percentage points. I also find a reduction of 2.0 percentage points in the probability of being paid by the hour with weekly earnings at or below the new threshold. These reductions are accompanied by an increase in the probability of not being employed (2.8 percentage points). Point estimates of the effects on being paid above the new threshold, either salaried or hourly, are very small and not statistically significant.

Incorporating task-based exemption measures into this analysis reveals that workers in high-exemption occupations may have been somewhat more exposed to the effects of changes in the salary level test threshold. Table 5 considers salaried workers in the pay ranges affected by threshold changes and adds an interaction between the difference-in-differences estimator and an indicator for having more than half of tasks classified as exempt within one's occupation. Workers in high-exemption occupations see a larger shift out of salaried jobs in the affected pay range, a reduction of about 9.1 percentage points compared with 5.7 percentage points for low-exemption occupations; that difference is marginally statistically significant.

Other outcomes show no significant differences between high- and low-exemption occupations, though the effect on non-employment is statistically different from zero for workers starting in high-exemption occupations but not for workers starting in low-exemption occupations. I also find at most small differences in hiring into high- vs. low-exemption occupations following threshold increases; estimates are reported in Table 6. Overall, the effects of raising the salary level test threshold appear to be modestly larger among but far from limited to workers in high-exemption occupations.

4.2.2 Managerial Titles, Exempt Tasks, and the Salary Level Test

Cohen et al. (2023) find and increased incidence of "fake-sounding" managerial job titles in job ads with salaries just above the salary level test threshold, a potential sign that employers use job titles strategically in an effort to have their workers classified as exempt from overtime coverage. Lack of data precluded consideration of the content of managerial jobs around this threshold. I revisit this topic using task-based exemption measures and task-tagged job ad data similar to that used in Section 4.1.3.

Rather than replicate the analysis in Cohen et al. (2023), I examine whether the prevalence of managerial job titles changes as income crosses the salary level test threshold and compare changes in title prevalence to changes in the content of jobs that have managerial titles.[18] I use job ad data from 2025 because salary information is available much more often in recent data than it was during the period covered by the original analysis. My analysis focuses on job ads with listed salaries within $2,500 of the annualized value of the salary level test threshold ($35,568) and non-missing employer ID and information about education and experience requirements. To limit computational requirements, I draw a 20 percent sample

[18] For this exercise, managerial job titles are those containing the terms manager, director, supervisor, chief, executive, president, vice, VP, head, lead, or principal.

of these ads and attach O*NET tasks using the TaskMatch module from JAAT, as above.

Visual inspection does not suggest that managerial job titles are sharply more prevalent above the salary level test threshold, or that the exempt content of jobs with managerial titles changes as income crosses the threshold. Figure 6 shows that, among jobs with at least 10 O*NET tasks attached to them, managerial titles are more common above the threshold than below, but there is no sharp change or clear excess mass near the threshold. The share of tasks that are exempt fluctuates across the few bins just above the threshold, first dropping sharply below and then rising sharply above the average level below the threshold; the exempt share ultimately stabilizes at roughly the below-threshold average.

Regression analysis that controls for salary, education and experience requirements, and employer fixed effects shows little change in the exempt content of managerial jobs across the salary level test threshold and no conclusive evidence of a change in the prevalence of such jobs. I estimate

$$y_{fj} = \alpha Above_j + \beta_1 Salary_j + \beta_2 \left(Salary_j \times Above_j \right) + \gamma X_j + \delta_f + \varepsilon_{fj} \tag{2}$$

where y_{fj} is either an indicator for a managerial job title or the share of tasks that are exempt, $Above_j$ is an indicator for salary above the salary level test threshold, $Salary_j$ is the deviation of the posted salary from the annualized salary level test threshold, X_j contains controls for minimum and maximum education and experience requirements, and δ_f is an employer fixed effect. The change in the outcome at the salary level test threshold is given by α. Table 7 reports results, with columns varying the number of attached tasks required for inclusion in the sample.

With ten or more tasks required, the point estimate for having a managerial job title is potentially economically meaningful, indicating an increase in prevalence above the threshold of about 3.4 percentage points. However, this effect is imprecisely estimated and disappears when task requirements are less stringent, which may be more appropriate for this outcome.

There are no notable changes in exempt content at any number of required tasks. If employers were attempting to avoid the duties test via "fake" managerial job titles, we would expect to see the prevalence of those titles increase above the salary level test threshold alongside a decline in the exempt content of managerial jobs. Though selection into wage posting can make analysis of job ads with salary information difficult to generalize, these estimates are not consistent with that story.

5 Conclusion

Overtime exemption status is determined for individual workers based on their primary duties and earnings, but these things are not measured together in any major datasets. Though factors like sector, occupation, or job title are not dispositive as to exemption status, analysts who wish to incorporate it are often forced to rely upon them as proxies. In this paper, I develop task-based measures of exemption status that build upon the O*NET framework, providing updated, continuous measures of exemption at the occupation level and enabling more nuanced analysis of exemption status in contexts where tasks are observed, such as in job ads or through future data collection.

Descriptively, task-based exemption measures reveal that about 60 percent of salaried workers are employed in occupations in which either no or all tasks are exempt. Task-based measures at the occupation level show somewhat greater degrees of exemption than existing occupation-level exemption measures used in regulatory analysis, especially in categories deemed unlikely to be exempt by those measures.[19] Incorporating task-based exemption measures into causal analyses also enhances the insights they produce. For example, the transition out of jobs affected by increases in state salary level test thresholds identified by Quach (2024) is somewhat more pronounced among workers in high-exemption occupations. Analysis of job titles around the salary level test threshold in the spirit of Cohen et al. (2023)

[19] Given that the existing exemption measures were produced in 1998, their alignment with the task-based measures is arguably surprisingly strong.

shows no change in the exempt content of managerial jobs across the threshold.

While recent overtime rulemaking has focused on changes to the salary level test, judicial decisions emerging from litigation around those efforts suggest that the salary level test needs to be closely linked to the duties test going forward. Task-based exemption measures could be useful for formulating or evaluating potential changes to the duties test. However, this paper suggests relatively limited scope for modest changes to the duties test to alter the range of acceptable salary level test thresholds. This is true under a wide range of assumptions about the within-occupation relationship between earnings and the performance of exempt work. Additional research, including efforts to measure workers' duties and earnings within the same datasets, would be helpful for evaluating these assumptions.

References

Bartik, Alexander W., Arpit Gupta, and Daniel Milo (2025). "The costs of housing regulation: Evidence from generative regulatory measurement." Working paper.

Brown, Charles C. and Daniel S. Hamermesh (2019). "Wages and hours laws: What do we know? What can be done?" Working Paper 25942, National Bureau of Economic Research. doi:10.3386/w25942.

Cohen, Lauren, Umit Gurun, and N. Bugra Ozel (2023). "Too many managers: The strategic use of titles to avoid overtime payments." Working Paper 30826, National Bureau of Economic Research. doi:10.3386/w30826. Revised May 2025.

Costa, Dora L. (2000). "Hours of work and the Fair Labor Standards Act: A study of retail and wholesale trade, 1938–1950." *Industrial and Labor Relations Review*, 53(4), pp. 648–664. doi:10.1177/001979390005300405.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock (2024). "GPTs are GPTs: Labor market impact potential of llms." *Science*, 384. doi:10.1126/science.adj0998.

Gilardi, Fabrizio, Meysam Alizadeh, and Maël Kubli (2023). "ChatGPT outperforms crowd workers for text-annotation tasks." *Proceedings of the National Academy of Sciences*, 120(30), p. e2305016,120. doi:10.1073/pnas.2305016120.

Goff, Leonard (2024). "Treatment effects in bunching designs: The impact of mandatory overtime pay on hours." *arXiv preprint arXiv:220510310*. Version 4, June 2024.

Hamermesh, Daniel S. and Stephen J. Trejo (2000). "The demand for hours of labor: Direct evidence from California." *Review of Economics and Statistics*, 82(1), pp. 38–47. doi:10.1162/003465300558614. Revision of NBER Working Paper No. 5973 (March 1997).

Heseltine, Michael and Bernhard Clemm von Hohenberg (2024). "Large language models as a substitute for human experts in annotating political text." *Research & Politics*, 11. doi:10.1177/20531680241236239.

Johnson, John H. (2003). "The impact of federal overtime legislation on public sector labor markets." *Journal of Labor Economics*, 21(1), pp. 43–69. doi:10.1086/344123.

Kim, Alex G., Maximilian Muhn, and Valeri Nikolaev (2024). "Financial statement analysis with large language models." Working paper.

Labaschin, Benjamin, Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock (2025). "Extending "GPTs are GPTs" to firms." *AEA Papers and Proceedings*, 115, pp. 51–55. doi:10.1257/pandp.20251045.

Le Mens, Gaël and Aina Gallego (2025). "Positioning political texts with large language models by asking and averaging." *Political Analysis*, 33(3), pp. 274–282. doi:10.1017/pan.2024.29.

Massenkoff, Maxim and Peter McCrory (2026). "Labor market impacts of AI: A new measure and early evidence." Anthropic Research.

Meisenbacher, Stephen, Svetlozar Nestorov, and Peter Norlander (2025). "Extracting O*NET features from the NLx corpus to build public use aggregate labor market data." *arXiv preprint arXiv:251001470*.

Pacific Legal Foundation (2024). "Robert Mayfield v. U.S. Department of Labor." Case page, Pacific Legal Foundation. Available at https://pacificlegal.org/case/doj-overtime-rule-nondelegation/.

Plano Chamber of Commerce, et al. v. United States Department of Labor, et al. (2024). United States District Court for the Eastern District of Texas, Sherman Division.

Quach, Simon (2024). "The labor market effects of expanding overtime coverage." Working paper, University of Southern California.

Quach, Simon (2025). "Wage hysteresis and entitlement effects: The persistent impacts of a temporary overtime policy." *The Quarterly Journal of Economics*, 140(2), pp. 1633–1680. doi:10.1093/qje/qjaf008.

Scheiber, Noam (2016). "Judge suspends rule expanding overtime for millions of workers." *The New York Times*. Available at https://www.nytimes.com/2016/11/22/business/obama-rule-to-expand-overtime-eligibility-is-suspended-by-judge.html.

Törnberg, Petter (2023). "ChatGPT-4 outperforms experts and crowd workers in annotating political Twitter messages with zero-shot learning." *arXiv preprint arXiv:230406588*.

Trejo, Stephen J. (1991). "The effects of overtime pay regulation on worker compensation." *American Economic Review*, 81(4), pp. 719–740.

Trejo, Stephen J. (2003). "Does the statutory overtime premium discourage long workweeks?" *Journal of Labor Economics*, 21(2), pp. 340–371. doi:10.1177/001979390305600310.

Wage and Hour Division, US Department of Labor (2004). "Defining and Delimiting the Exemptions for Executive, Administrative, Professional, Outside Sales and Computer Employees." 69 Fed. Reg. 22122. Codified at 29 C.F.R. Part 541.

Wage and Hour Division, US Department of Labor (2019). "Defining and Delimiting the Exemptions for Executive, Administrative, Professional, Outside Sales and Computer Employees." 84 Fed. Reg. 51230. Codified at 29 C.F.R. Part 541, available at https://www.govinfo.gov/content/pkg/FR-2019-09-27/pdf/2019-20353.pdf.

Wage and Hour Division, US Department of Labor (2024). "Defining and Delimiting the Exemptions for Executive, Administrative, Professional, Outside Sales and Computer Employees." 89 Fed. Reg. 32838. Codified at 29 C.F.R. Part 541; vacated by *Plano Chamber of Commerce v. DOL*, No. 4:24-CV-499 (E.D. Tex. Nov. 15, 2024).

Tables

Table 1: Descriptions of Duties Relevant to White-Collar Exemptions

Exemption	**Qualifying Duties**
Executive	Primary duty is managing the enterprise, or a customarily recognized department or subdivision thereof. Must customarily and regularly direct the work of two or more full-time employees (or the equivalent), and must have authority to hire or fire other employees, or have recommendations on hiring, firing, advancement, or promotion given particular weight.
Administrative	Primary duty is office or non-manual work directly related to management or the general business operations of the employer or its customers. Primary duty must include the exercise of discretion and independent judgment with respect to matters of significance—as distinct from applying well-established techniques or procedures under close supervision.
Professional	Primary duty is either: (*i*) work requiring advanced knowledge in a field of science or learning customarily acquired by a prolonged course of specialized intellectual instruction (learned professional), or (*ii*) work requiring invention, imagination, originality, or talent in a recognized field of artistic or creative endeavor (creative professional). In both cases the work must predominantly involve the consistent exercise of discretion and judgment.

Notes: Sources: 29 CFR §§ 541.100, 541.200, 541.300; DOL Fact Sheets #17B, #17C, #17D.

Table 2: Mean Exemption Share by DOL Probability Code, Salaried Workers, 2025

DOL prob. code	Workers (avg. monthly, millions)	Mean share of tasks classified exempt (%) Equal weights	IM weighted	RT weighted	Freq (ordinal)	Freq (weekly)	Freq (daily+)	RT× Freq
Panel A: Mean share of tasks classified exempt (%)								
0 (0%)	10.16	4.2	4.5	4.3	4.4	4.6	4.7	4.4
1 (90–100%)	32.30	87.3	87.6	87.9	87.6	87.5	86.8	87.6
2 (50–90%)	8.41	63.9	64.3	64.6	64.5	64.0	64.0	64.5
3 (10–50%)	6.17	35.6	39.3	39.5	39.3	39.0	38.8	39.3
4 (0–10%)	6.49	10.3	10.5	10.3	10.4	10.8	10.7	10.4
All	63.54	58.0	58.6	58.8	58.7	58.6	58.2	58.7
Panel B: Share of workers in occupations with >50% of tasks classified exempt (%)								
0 (0%)	10.16	4.9	4.9	4.9	4.9	5.4	5.4	4.9
1 (90–100%)	32.30	95.8	92.9	92.9	93.0	93.0	93.0	93.0
2 (50–90%)	8.41	76.5	72.4	72.4	72.7	72.7	72.7	72.7
3 (10–50%)	6.17	45.1	45.1	45.1	44.5	44.5	44.5	44.5
4 (0–10%)	6.49	13.4	13.4	13.4	13.4	13.4	13.4	13.4
All	63.54	65.4	63.4	63.3	63.4	63.5	63.4	63.4

Notes: DOL probability codes are from DOL regulatory impact analyses and classify occupations by probability of exemption from FLSA overtime requirements. Exemption shares are based on tasks from version 30.2 of the O*NET database. Means across workers are weighted by outgoing rotation weights. Within-occupation shares of tasks classified as exempt are constructed using several weighting schemes, listed at the top of the relevant columns: equal weights (unweighted task share); IM weighted (importance-weighted); RT weighted (relevance-weighted); Freq ordinal (ordinal frequency ratings); Freq weekly (times-per-week ratings); Freq daily+ (share of tasks performed daily or more); RT×Freq (relevance-times-frequency composite). Panel B reports the share of workers employed in an occupation where more than 50% of tasks are classified as exempt under each respective measure. Sample is restricted to salaried workers.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, DOL probability codes, task exemption classifications, and author's calculations.

Table 3: Share of Duties-Test-Passing Salaried Workers Below the Salary Threshold, by Subgroup and Threshold, 2025

		% salaried below	DOL	$P(w < T \mid s \geq s^*)$: share of duties-test passers ($s \geq s^*$) with earnings w below threshold T														
				Occupation-level s^*					Factor model 1, individual s^*					Factor model 2, individual s^*				
Threshold	Subgroup	threshold	(gamma)	0.10	0.25	0.50	0.75	0.90	0.10	0.25	0.50	0.75	0.90	0.10	0.25	0.50	0.75	0.90
\$684/wk	All salaried	7.6	4.4	5.7	5.7	5.8	5.2	5.9	5.8	5.8	5.8	5.8	6.4	5.8	5.8	5.8	6.1	6.6
	Low-wage industries	3.9	8.0	10.6	10.5	10.6	8.8	9.2	10.6	10.6	10.6	9.0	9.6	10.6	10.6	10.6	9.5	9.7
	Non-metro	0.9	7.2	9.1	9.1	9.3	8.6	9.4	9.2	9.2	9.3	8.9	9.6	9.2	9.2	9.3	9.4	10.5
	Census South	3.3	5.0	6.3	6.3	6.4	5.6	6.4	6.4	6.4	6.5	6.4	6.8	6.4	6.4	6.5	6.5	6.9
\$844/wk	All salaried	11.7	7.1	9.0	8.9	9.0	8.1	8.9	9.1	9.1	9.2	8.8	9.5	9.1	9.1	9.1	9.3	10.0
	Low-wage industries	5.6	12.2	15.8	15.8	15.9	13.3	13.8	15.9	15.9	15.9	13.6	14.4	15.9	15.9	15.9	14.3	14.6
	Non-metro	1.4	10.9	13.7	13.7	13.7	12.7	13.3	13.9	13.9	13.9	13.3	14.0	13.9	14.0	14.0	13.9	15.2
	Census South	5.2	8.3	10.3	10.2	10.4	9.2	10.3	10.4	10.5	10.5	10.3	11.0	10.4	10.5	10.5	10.7	11.4
\$913/wk	All salaried	14.0	8.7	10.9	10.8	10.9	9.9	10.9	11.1	11.1	11.1	10.9	11.7	11.1	11.1	11.1	11.4	12.2
	Low-wage industries	6.5	14.7	18.8	18.7	18.9	16.1	16.9	18.9	18.9	18.9	16.6	17.8	18.9	18.9	18.9	17.5	17.9
	Non-metro	1.7	14.0	17.3	17.4	17.2	16.1	17.4	17.5	17.5	17.4	17.1	18.6	17.5	17.6	17.4	18.1	20.2
	Census South	6.3	10.4	12.6	12.5	12.7	11.4	12.6	12.9	12.9	12.9	12.6	13.5	12.9	12.9	12.9	13.1	14.0
\$1128/wk	All salaried	22.9	15.9	19.0	18.8	18.9	17.7	19.5	19.3	19.2	19.1	19.1	20.7	19.3	19.2	19.1	20.0	21.6
	Low-wage industries	10.2	26.4	31.2	31.1	31.2	28.2	30.3	31.3	31.3	31.3	29.1	31.8	31.3	31.3	31.2	30.6	32.0
	Non-metro	2.6	23.7	27.8	27.5	27.3	25.8	27.6	28.0	27.8	27.5	27.1	29.1	28.0	27.8	27.4	28.3	31.4
	Census South	10.5	19.9	23.0	22.8	23.1	21.8	24.3	23.2	23.2	23.3	23.8	26.2	23.2	23.2	23.2	24.8	27.3

Notes: Each cell reports the share of expected exempt workers in the indicated group earning below the salary threshold T. The DOL (gamma)column implements a version of methodology used in the regulatory impact analysis accompanying the 2023 notice of proposed rulemaking: Probability codes assign each occupation a range of exemption probability (code 1: 90–100%; code 2: 50–90%; code 3: 10–50%; code 4: 0–10%), and each worker's individual exemption probability is $p_i = \ell_k + (u_k - \ell_k) \cdot F_\Gamma(w_i;\, \alpha, \beta)$, where ℓ_k, u_k are the bounds for code k, $\alpha = (\bar{w}/\sigma)^2$, $\beta = \sigma^2/\bar{w}$ estimated from non-top-coded salaried workers. Top-coded workers receive $p_i = u_k$. This column reports $\sum_i p_i w_i \mathbf{1}(earn_i < T) \,/\, \sum_i p_i w_i$, the probability-weighted share earning below T. In the remaining columns, workers pass the duties test if the share of their job that is exempt exceeds a given threshold s^*, which varies across columns. In the occupation-level s^* columns, workers are assigned the share of exempt tasks associated with their occupation. In the factor model columns, task performance is simulated and exempt taks shares are calculated at the individual level. See Appendix B for factor model details and parameterization. Model 1 is meant to represent a scenario in which there is some specialization by workers in exempt work and a moderate, positive within-occupation correlation between earnings and performance of exempt work ($\lambda_G = 0.3, \lambda_X = 0.5, \rho_G = 0.3, \rho_X = 0.6$). Model 2 represents a scenario with more specialization and a more strongly positive correlation between earnings and exempt work ($\lambda_G = 0.3, \lambda_X = 0.7, \rho_G = 0.3, \rho_X = 0.8$). Sample includes salaried workers with valid earnings in CPS outgoing rotation groups. Subgroups are mean to align with those considered by the Kantor test. Low-wage industries are those with weighted mean salaried earnings in the bottom third of major industry groups.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, DOL probability codes, task exemption classifications, and author's calculations.

Table 4: Effects of State Salary Level Test Threshold Changes on Employment Transitions

	(1) Sal.≤new	(2) Sal.>new	(3) Hrly.≤new	(4) Hrly.>new	(5) Not empl.
Panel A: Salaried workers, earnings in [old, new) range					
Treat × After	-0.0780***	-0.0182.	0.0398***	0.0445***	0.0119.
	(0.0153)	(0.0116)	(0.0094)	(0.0104)	(0.0131)
N	46,429	46,429	46,429	46,429	46,429
Panel B: Previously unemployed workers (hires)					
Treat × After	-0.0136***	0.0044.	-0.0198**	0.0012.	0.0278**
	(0.0038)	(0.0059)	(0.0079)	(0.0043)	(0.0116)
N	114,009	114,009	114,009	114,009	114,009

Notes: Sample includes workers observed twice in CPS outgoing rotation groups, before and after changes in state salary level test thresholds. Outcome variables are binary indicators for whether a worker has a salaried (sal) or hourly (hrly) job at or below vs above the new salary level test threshold, or is not employed. Effects are estimated using the stacked difference-in-differences analysis of 19 state-level overtime salary threshold increases from 2014–2021 described in equation 1, following Quach (2024). Panel A: treated workers are salaried, in the state raising its threshold, with weekly earnings in [old threshold, new threshold) for that event. Panel B: treated workers are unemployed in the pre-year. Control workers in both panels are those with the same employment status in non-treatment states. Ever-treated states (AK, CA, CO, ME, NY, and WA) are excluded from the control pool for all events. Regression includes event × state and event × period FEs, as well as age, sex, race/ethnicity, and education fixed effects. Standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Current Population Survey Outgoing Rotation Groups, and author's calculations.

Table 5: Effects of State Salary Level Test Threshold Changes on Employment Transitions, Incorporating Task-Based Exemption Status

	(1)	(2)	(3)	(4)	(5)
	Sal.≤new	Sal.>new	Hrly.≤new	Hrly.>new	Not empl.
Treat × After (low exempt)	-0.0568***	-0.0055.	0.0315**	0.0327*	-0.0019.
	(0.0203)	(0.0294)	(0.0141)	(0.0195)	(0.0218)
Treat × After × High exempt	-0.0344*	0.0030.	-0.0076.	0.0163.	0.0227.
	(0.0189)	(0.0299)	(0.0135)	(0.0187)	(0.0188)
Implied DiD for high-exempt workers (sum of above):					
Treat × After (high exempt)	-0.0913***	-0.0025.	0.0239*	0.0490***	0.0208***
	(0.0159)	(0.0077)	(0.0140)	(0.0058)	(0.0066)
N	46,429	46,429	46,429	46,429	46,429

Notes: Sample includes workers observed twice in CPS outgoing rotation groups, before and after changes in state salary level test thresholds. Outcome variables are binary indicators for whether a worker has a salaried (sal) or hourly (hrly) job at or below vs above the new salary level test threshold, or is not employed. Effects are estimated using a stacked triple difference analysis of 19 state-level overtime salary threshold increases from 2014–2021, incorporating task-based exemption measures into analysis in the style of Quach (2024). Treated workers are salaried, in the state raising its threshold, with weekly earnings in [old threshold, new threshold) for that event. Control workers are those with the same salary status in non-treatment states. Ever-treated states (AK, CA, CO, ME, NY, and WA) are excluded from the control pool for all events. High-exempt workers are those in occupations with more than half of tasks classified as exempt. Regression includes event × state and event × period FEs, as well as age, sex, race/ethnicity, and education fixed effects. Standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, task exemption classifications, and author's calculations.

Table 6: Effects of State Salary Level Test Threshold Changes on Hires by Type of Job, Previously Unemployed Workers

	(1) Sal.≤new	(2) Sal.>new	(3) Hrly.≤new	(4) Hrly.>new	(5) Not empl.
High-exempt occ.	-0.0086***	0.0016.	-0.0085**	-0.0002.	0.0278**
	(0.0025)	(0.0032)	(0.0042)	(0.0014)	(0.0116)
N	114,009	114,009	114,009	114,009	114,009
Low-exempt occ.	-0.0051*	0.0028.	-0.0112**	0.0014.	
	(0.0029)	(0.0040)	(0.0057)	(0.0037)	
N	114,009	114,009	114,009	114,009	

Notes: Sample includes workers observed twice in CPS outgoing rotation groups, before and after changes in state salary level test thresholds. Outcome variables are binary indicators for having a job with the indicated characteristics. Columns indicate salaried vs. hourly status and earnings relative to the new salary level test threshold. Rows indicate the share of tasks that are exempt within the occupation in which workers are employed. High-exempt occupations have at least 50 percent of tasks classified as exempt. Effects are estimated using the stacked difference-in-differences analysis of 19 state-level overtime salary threshold increases from 2014–2021 described in equation 1, following Quach (2024). Treated workers are unemployed in the pre-period in a state raising its salary level test threshold. Control workers are unemployed in non-treatment states. Ever-treated states (AK, CA, CO, ME, NY, and WA) are excluded from the control pool for all events. Column 5 (not employed) has no destination occupation and is reported once alongside the high-exempt row. Regression includes event × state and event × period FEs, as well as age, sex, race/ethnicity, and education fixed effects. Standard errors clustered at the state level, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, task exemption classifications, and author's calculations.

Table 7: Above-Threshold Effects on Managerial Classification and Exempt Task Share (All Full-Time Ads, ±\$2,500 around \$35,568/yr)

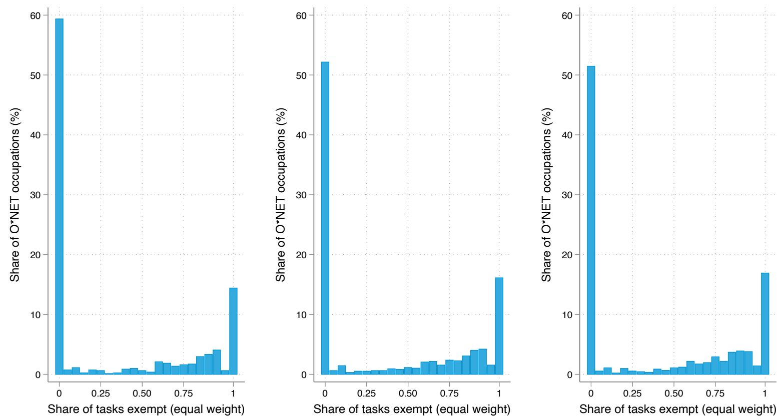
	Managerial title			*Exempt task share*		
	(1)	(2)	(3)	(4)	(5)	(6)
Minimum tasks	≥1	≥5	≥10	≥1	≥5	≥10
Above threshold	-0.0061	0.0030	0.0339	0.0066	-0.0034	-0.0023
(≥ \$35,568/yr)	(0.0112)	(0.0209)	(0.0405)	(0.0064)	(0.0064)	(0.0090)
N	57,523	29,435	13,618	57,523	29,435	13,618
R^2	0.498	0.516	0.485	0.468	0.500	0.566

Notes: Sample includes all ads from 2025 for full-time jobs with annual salary within \$2,500 of the annualized value of the current salary level test threshold (\$35,568/yr = \$684/wk) and non-missing education and experience requirements and employer IDs. *Above threshold* = 1 if posted annual salary ≥ \$35,568. *Managerial title* = 1 if the job title contains a management keyword (manager, director, supervisor, chief, executive, president, vice, VP, head, lead, principal). *Exempt task share*: mean equal-weighted exempt task share across matched O*NET tasks. Per equation 2, salary enters as a deviation from threshold ($salary_c = salary - \$35,568$) with a separate linear slope on each side of the threshold (via $salary\_c \times above\_threshold$ interaction). The minimum tasks row indicates the minimum number of O*NET tasks that must be matched to a job ad in order for it to be included in the sample. All columns include controls for salary, and minimum/maximum education and experience requirements, and employer fixed effects. Standard errors are clustered by employer. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
Source: Lightcast, O*NET, task exemption classifications, and author's calculations.

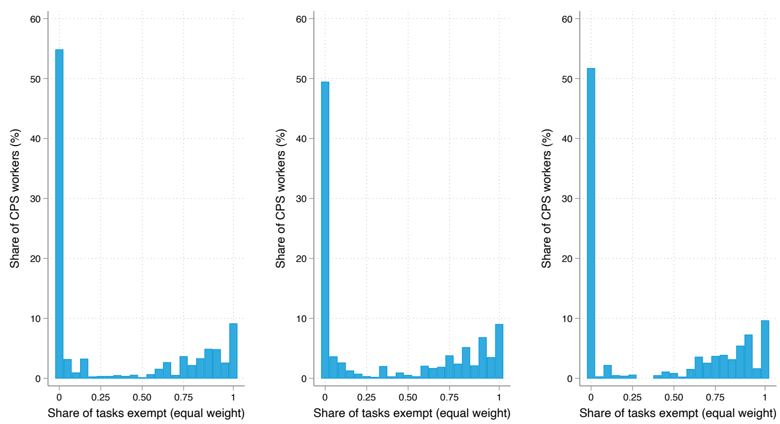
Figures

Figure 1: Share of Tasks Classified as Exempt by O*NET Occupation

(a) Occupation weighted

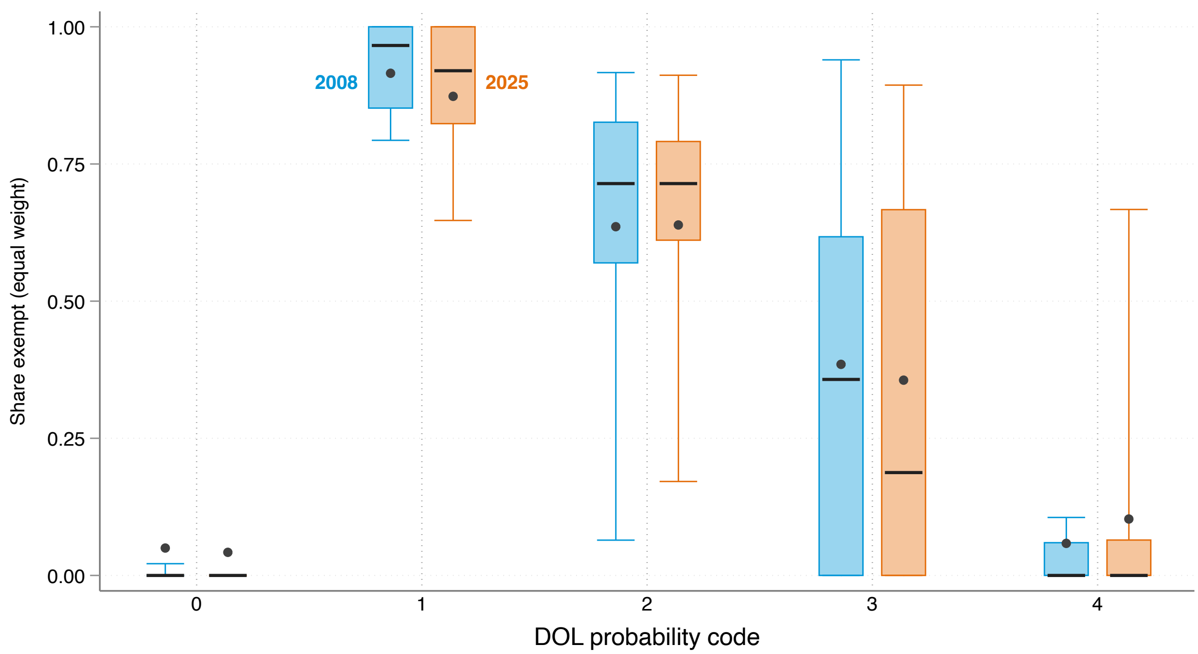


(b) Worker weighted



Notes: Histograms of the equal-weight task exemption measure (share of tasks classified as exempt) at the occupation level (panel a) and among CPS workers (panel b) for O*NET vintages 2008, 2016, and 2025. Bins: 0 and 1 are exact mass points; interior bins are 0.05 wide. Panel (b) uses CPS outgoing rotation workers with positive earnings, weighted by person-weight.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, task exemption classifications, and author's calculations.

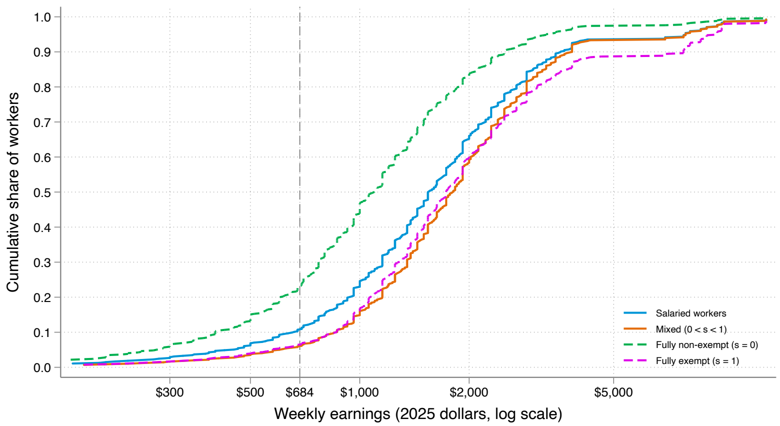
Figure 2: Share of O*NET Tasks Classified as Exempt by DOL Exemption Probability Code



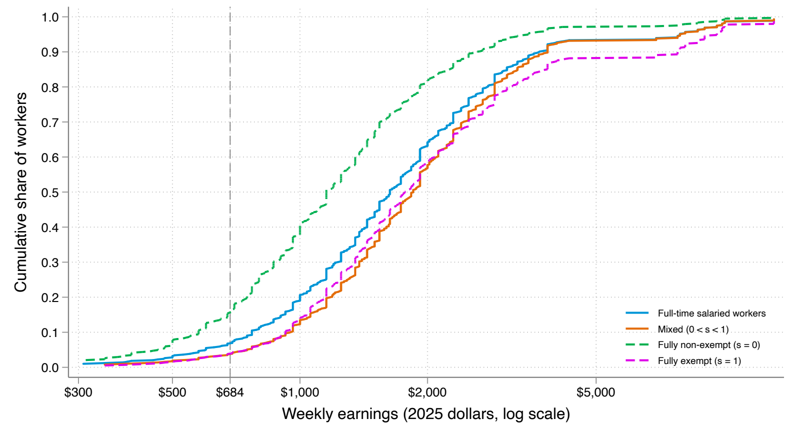
Notes: Sample includes salaried workers with positive earnings. Box = IQR (25th–75th percentile); line = median; whiskers = 10th/90th percentile; dot = mean. Moments are calculated using sample weights. DOL probability codes correspond with probabilities of being exempt from overtime coverage, as indicated.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, DOL probability codes, task exemption classifications, and author's calculations.

Figure 3: Distribution of Weekly Earnings by Occupation-Level Exemption Status

(a) All Salaried Workers



(b) Full-Time Salaried Workers

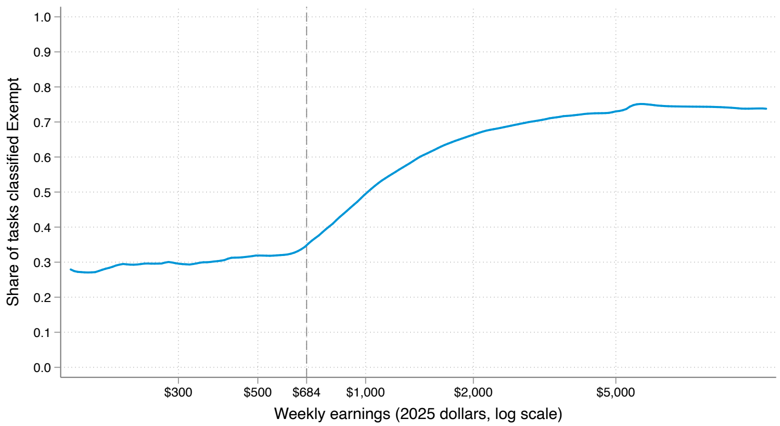


(c) Full-Time Salaried Workers in South

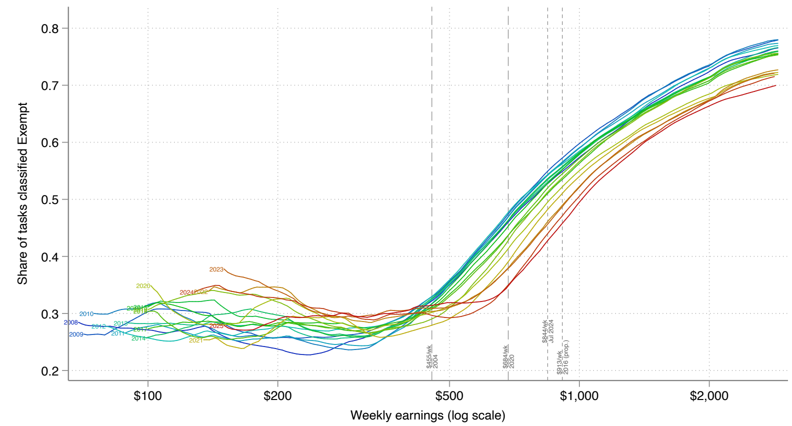
Notes: Figures show the weighted empirical CDF of weekly earnings (2025 dollars, log scale) by occupation-level exemption status group. Occupation-level exempt task shares s are calculated giving equal weight to each task. Groups: fully non-exempt ($s = 0$), mixed ($0 < s < 1$), fully exempt ($s = 1$). The value of the salary level test threshold ($684/wk) is shown as a vertical dashed line.

Figure 4: Average Share of O*NET Tasks Classified as Exempt by Weekly Earnings, Salaried Workers

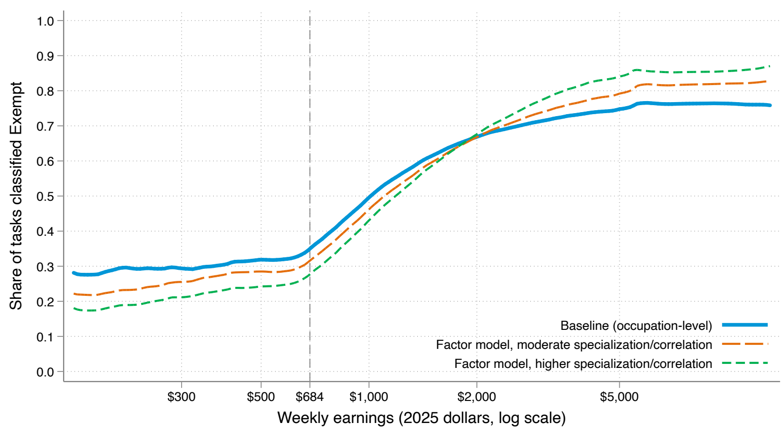
(a) Occupation-level, equal weight, 2025



(b) Occupation-level, equal weight, all years

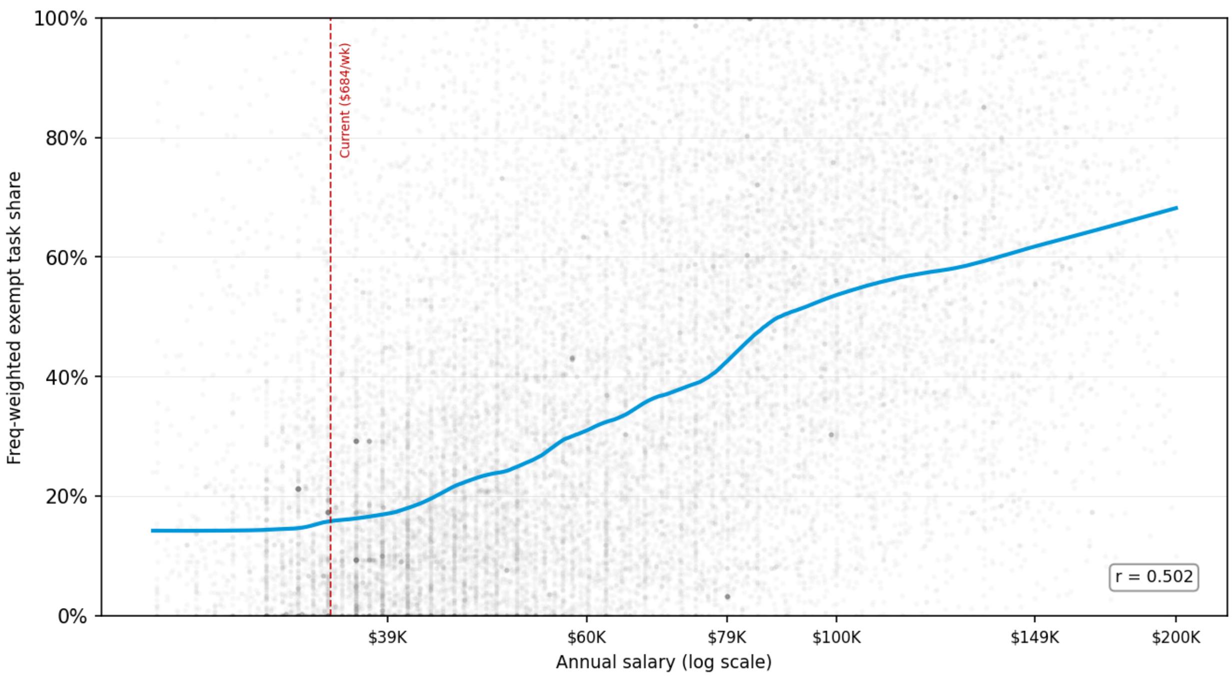


(c) Individual-level simulations, 2025



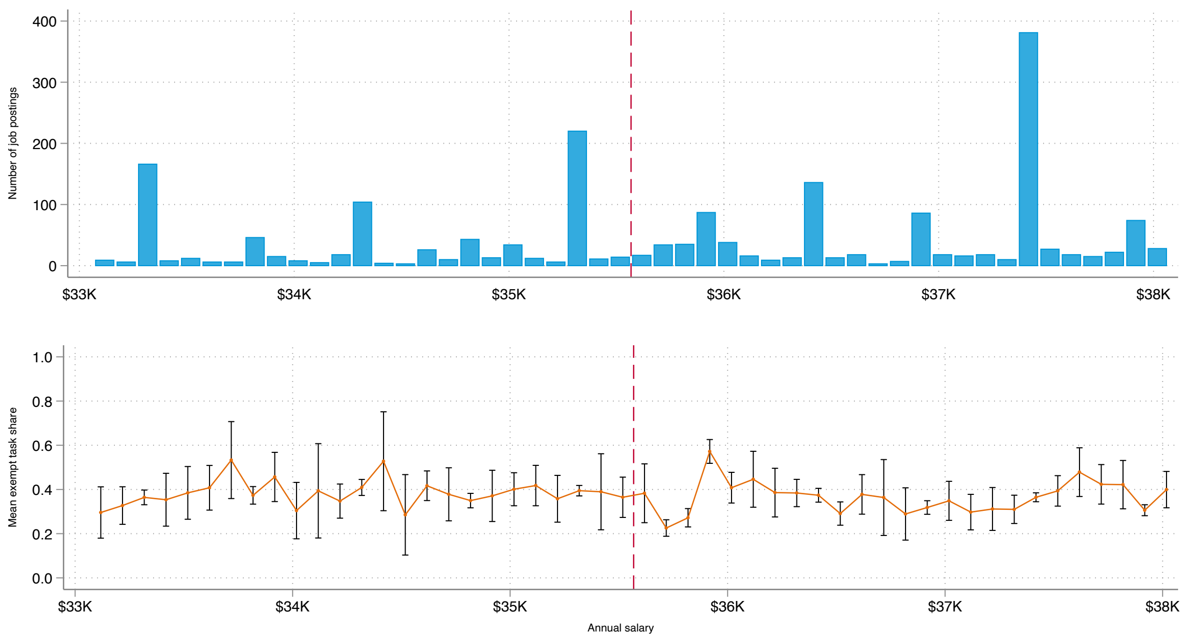
Notes: Figures show occupation-level equal-weight task exemption shares against weekly earnings (log scale), smoothed via kernel-weighted local polynomial smoothing; sample includes salaried workers only. Salary level test threshold ($684/wk) shown as vertical dashed line. Panel (a) shows data for 2025. Panel (b) shows a separate line for each year from 2008–2025, colored blue (2008) to red (2025); dashed vertical lines show salary thresholds in effect (solid) or proposed but not enacted (short-dash); 2023–2025 series truncated at pre-2023 topcode ceiling ($2,900/wk). Panel (c) compares the baseline plot for 2025 to versions produced based on simulations generated by the factor model described in Section 4.1.3 and Appendix B. The long-dashed orange line is based on parameters $\{\lambda_G = 0.3, \lambda_X = 0.5, \rho_G = 0.3, \rho_X = 0.6\}$. The shorter-dashed green line is based on parameters $\{\lambda_G = 0.3, \lambda_X = 0.7, \rho_G = 0.3, \rho_X = 0.8\}$.

Figure 5: Average Share of O*NET Tasks Classified as Exempt by Weekly Earnings, Job Ads



Notes: Local polynomial smoothing of job-ad-level equal-weight task exemption share against weekly earnings (log scale) for a 1 percent sample of job ads posted during 2025. Sample is restricted to ads for full-time jobs with at least 10 O*NET tasks associated with them by the Job Ads Analysis Toolkit TaskMatch module; see Meisenbacher et al. (2025) for details. Annualized value of the salary level test threshold ($684/wk) shown as vertical dashed line.

Figure 6: Managerial Job Titles and Exempt Tasks Near the Salary Level Test Threshold



Notes: Analysis is based on a 20 percent sample of ads from 2025 for full-time jobs with non-missing education and experience requirement information, employer ID, salary within $2,500 of the annualzed value of the salary level test threshold ($35,568, plotted as a dashed vertical line), and at least 10 O*NET tasks associated with them by the Job Ads Analysis Toolkit TaskMatch module; see Meisenbacher et al. (2025) for details. Ads are placed in $100 bins. The top panel shows the number of ads with managerial job titles (titles containing the terms manager, director, supervisor, chief, executive, president, vice, VP, head, lead, or principal) in each bin. The bottom panel shows the average share of tasks that are exempt within each bin.
Source: Lightcast, O*NET, task exemption classifications, and author's calculations.

Appendix A Task Exemption Status Classification Details

Appendix A.1 LLM Instructions

The following instructions were provided, verbatim as a Word document, to the LLM for classifying the exemption status of O*NET tasks:

*As you know, exemption from FLSA overtime protections is typically determined based on a combination of factors, including job duties, salary level, and how the employee is paid. I'm conducting a study that focuses on the duties test and how individual job tasks—like those listed in O*NET—might influence exemption determinations.*

I recognize that exemption status cannot be determined solely from a single task in isolation. However, I'm interested in your expert judgment about the directional relevance of specific tasks.

*You will be presented with a series of occupation-task pairs. For each pair, you should answer the following question: Suppose a full-time salaried employee working as [occupation] performs the following task frequently or as a primary part of their job: [Insert O*NET task description here.] Does this task suggest that the employee is more likely to be classified as exempt or non-exempt under the FLSA overtime rules, assuming all other factors are held constant and the worker's overtime exemption status is not already determined by some other factor?*

You will also be asked to provide the specific exemption that is most relevant to any tasks that make workers more likely to be exempt, and any additional explanation that is necessary to understand your answers. Output should be provided in the form of a spreadsheet that lists the provided occupation in the first column, the provided task in the second column, the exempt/non-exempt determination in the third column, the relevant exemption in the fourth column, and any additional explanation in the fifth column.

Consider all the background information about how overtime exemption is determined *that is provided in the documents included in this project. Consider each occupation-task pair one at a time, in isolation. Your answer to the question about exemption status should be either "Exempt" or "Non-exempt." No other value is acceptable.*

If the task is more likely to make a worker exempt, provide the specific exemption that is most relevant to the task.

If additional explanation is required to understand the determination of the exemption status associated with a task, provide that as well.

Appendix A.2 Additional Background Documents

The LLM was also provided with the following documents as background information:

- The FLSA statute
- The 2019 overtime final rule
- Wage and Hour Division Field Assistance Bulletin 2010-2
- Wage and Hour Division Field Assistance Bulletins 2006-3, 2007-2, 2010-2, 2018-1, and 2021-3
- Wage and Hour Division Fact Sheets 17A, 17B, 17C, 17D, 17E, 17F, 17G, and 17H, as updated August 2024
- Wage and Hour Division Administrator's Interpretation 2010-1
- Wage and Hour Division Field Operations Handbook chapters 11, 22, 23, 24, 25, and 32

Appendix B Latent Factor Model Details

In Section 4.1.3, I use a latent factor model to simulate task performance at the individual level. The model uses two latent factors: general task intensity (f_G) and exempt-task specialization (f_X). Each worker's values of these factors are functions of the worker's earnings rank within their occupation:

$$f_{iG} = \rho_G \cdot \Phi^{-1}(r_i) + \sqrt{1-\rho_G^2} \cdot \eta_{iG} \tag{B1}$$

$$f_{iX} = \rho_X \cdot \Phi^{-1}(r_i) + \sqrt{1-\rho_X^2} \cdot \eta_{iX} \tag{B2}$$

Here, ρ_G is the correlation between the general task intensity factor and earnings, ρ_X is the correlation between the exempt-task specialization factor and earnings, $\Phi^{-1}(r_i)$ is the transformation of the worker's within-occupation earnings rank r_i into a standard normal score, and η_{iG} and η_{iX} are IID standard normal error terms.

Each worker-task pair, then, has a latent score

$$z_{it} = \lambda_G \cdot f_{iG} + sign(E_t) \cdot \lambda_X \cdot f_{iX} + \sigma_\varepsilon \cdot \varepsilon_{it} \tag{B3}$$

where λ_G and λ_X are the loadings of the general and specialization factors, respectively, $\sigma_\varepsilon = \sqrt{1-\lambda_G^2-\lambda_X^2}$, and $sign(E_t)$ is positive if task t is exempt and negative if it is non-exempt. The score z_{it} is then mapped to frequency of performance via $u_{it} = \Phi(z_{it})$, which is treated as a percentile and aligned with O*NET frequency categories. A worker i performs task t if the assigned frequency category is at least "weekly or more often," and worker i's exempt task share $\tilde{E}_i$ is the fraction of tasks performed by i that are classified as exempt.

In this exercise, I fix ρ_G at 0.3, which corresponds to a modestly positive correlation between earnings and general task intensity of workers' jobs, and consider various values of ρ_X, λ_G, and λ_X. The $\{\lambda_G, \lambda_X, \rho_X\}$ triples I consider are $\{0.5, 0.3, -0.3\}$, $\{0.5, 0.3, 0.0\}$, $\{0.5, 0.3, 0.3\}$, $\{0.5, 0.3, 0.6\}$, $\{0.3, 0.5, -0.3\}$, $\{0.3, 0.5, 0.0\}$, $\{0.3, 0.5, 0.3\}$, $\{0.3, 0.5, 0.6\}$, and

$\{0.3, 0.7, 0.8\}$. The tables that report results for individual simulations focus on the last two, which impose the greatest degree of exempt-task specialization and the strongest within-occupation correlation between earnings and exempt task performance of the parameter sets considered.

Appendix C Additional Tables and Figures

Table C1: High-Exemption Threshold Shares by DOL Probability Code — Salaried Workers (CPS 2025)

DOL prob. code	Workers (avg. monthly, millions)	Equal weights	IM weighted	RT weighted	Freq (ordinal)	Freq (weekly)	Freq (daily+)	RT× Freq
		Mean share of tasks classified exempt (%)						
Panel A: Share of workers in occupations with ≥75% of tasks classified exempt (%)								
0 (0%)	10.16	1.6	4.7	1.6	4.7	4.7	4.7	4.7
1 (90–100%)	32.30	87.1	83.7	84.3	84.4	80.0	80.2	84.4
2 (50–90%)	8.41	30.2	30.7	30.6	28.6	37.1	28.9	28.6
3 (10–50%)	6.17	19.8	19.8	19.8	21.4	22.5	16.4	21.4
4 (0–10%)	6.49	1.4	1.4	1.4	1.4	10.0	10.0	1.4
All	63.54	50.6	49.4	49.2	49.7	49.6	48.0	49.7
Panel B: Share of workers in occupations with ≥90% of tasks classified exempt (%)								
0 (0%)	10.16	1.6	1.6	1.6	1.6	1.6	0.0	1.6
1 (90–100%)	32.30	50.9	51.0	50.8	50.9	52.5	52.8	50.9
2 (50–90%)	8.41	19.6	19.6	19.6	19.6	25.4	25.4	19.6
3 (10–50%)	6.17	9.0	9.5	10.7	10.7	9.5	9.2	10.7
4 (0–10%)	6.49	0.0	0.0	0.0	0.0	0.0	0.0	0.0
All	63.54	29.6	29.7	29.7	29.8	31.2	31.1	29.8

Notes: DOL probability codes as in Table 2. Sample is restricted to salaried workers. Panel A reports the share of workers employed in an occupation where ≥75% of tasks are classified as exempt under each measure. Panel B reports the share where ≥90% of tasks are classified as exempt. Worker counts and weighting as in Table 2.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, DOL probability codes, task exemption classifications, and author's calculations.

Table C2: Duties-Test-Passing Salaried Workers (Millions) by Salary Threshold and Subgroup (CPS 2025)

				Workers passing duties test (millions)														
		All salaried (millions)	DOL (gamma)	Occupation-level s^*					Factor model 1, individual s^*					Factor model 2, individual s^*				
Threshold	Subgroup			0.10	0.25	0.50	0.75	0.90	0.10	0.25	0.50	0.75	0.90	0.10	0.25	0.50	0.75	0.90
Any earnings	All salaried	53.38	39.34	44.06	43.13	41.04	31.99	18.63	42.82	42.23	40.54	23.77	15.68	42.96	42.24	40.66	21.06	14.14
	Census South	20.28	14.47	16.34	15.95	15.13	11.85	6.83	15.89	15.63	14.97	8.65	5.74	15.95	15.64	15.01	7.70	5.15
	Non-metro	4.34	2.97	3.48	3.39	3.27	2.51	1.53	3.43	3.37	3.25	1.96	1.32	3.45	3.38	3.26	1.72	1.21
	Low-wage industries	15.77	11.25	13.69	13.55	13.20	10.48	7.63	13.57	13.47	13.23	9.26	6.71	13.59	13.47	13.24	8.14	6.62
\$684/wk	All salaried	4.05	1.75	2.51	2.44	2.36	1.67	1.11	2.49	2.45	2.37	1.38	1.00	2.50	2.45	2.37	1.28	0.94
	Census South	1.77	0.73	1.03	1.00	0.97	0.67	0.44	1.02	1.00	0.97	0.55	0.39	1.02	1.00	0.97	0.50	0.36
	Non-metro	0.48	0.21	0.32	0.31	0.30	0.21	0.14	0.32	0.31	0.30	0.18	0.13	0.32	0.31	0.30	0.16	0.13
	Low-wage industries	2.07	0.90	1.45	1.42	1.40	0.92	0.70	1.44	1.43	1.40	0.84	0.65	1.44	1.43	1.40	0.78	0.64
\$844/wk	All salaried	6.26	2.78	3.95	3.82	3.68	2.58	1.66	3.92	3.86	3.71	2.10	1.49	3.93	3.86	3.72	1.95	1.41
	Census South	2.78	1.20	1.67	1.62	1.57	1.09	0.70	1.66	1.63	1.58	0.89	0.63	1.66	1.64	1.58	0.82	0.59
	Non-metro	0.73	0.32	0.48	0.47	0.45	0.32	0.20	0.48	0.47	0.45	0.26	0.19	0.48	0.47	0.46	0.24	0.18
	Low-wage industries	2.98	1.37	2.17	2.14	2.10	1.39	1.05	2.16	2.14	2.10	1.26	0.97	2.16	2.14	2.11	1.16	0.97
\$913/wk	All salaried	7.47	3.42	4.81	4.65	4.47	3.16	2.03	4.77	4.69	4.49	2.59	1.83	4.78	4.69	4.50	2.40	1.73
	Census South	3.34	1.50	2.06	2.00	1.93	1.36	0.86	2.04	2.01	1.93	1.09	0.77	2.05	2.01	1.93	1.01	0.72
	Non-metro	0.88	0.41	0.60	0.59	0.56	0.40	0.27	0.60	0.59	0.57	0.33	0.25	0.60	0.59	0.57	0.31	0.24
	Low-wage industries	3.46	1.66	2.58	2.54	2.49	1.69	1.29	2.56	2.54	2.49	1.53	1.19	2.57	2.54	2.50	1.42	1.19
\$1,128/wk	All salaried	12.24	6.27	8.36	8.11	7.75	5.66	3.63	8.24	8.10	7.75	4.55	3.24	8.28	8.11	7.76	4.22	3.06
	Census South	5.60	2.87	3.75	3.64	3.50	2.59	1.66	3.69	3.63	3.48	2.06	1.50	3.70	3.64	3.49	1.91	1.40
	Non-metro	1.39	0.70	0.97	0.93	0.89	0.65	0.42	0.96	0.94	0.89	0.53	0.38	0.96	0.94	0.90	0.49	0.38
	Low-wage industries	5.43	2.97	4.27	4.21	4.12	2.96	2.31	4.25	4.22	4.13	2.69	2.13	4.26	4.22	4.14	2.49	2.12

Notes: Each cell reports the number of workers (in millions) in the indicated group passing the duties test. The "All salaried" column reports total salaried workers in the subgroup: for the "Any earnings" rows, this is all salaried workers with valid earnings; for the threshold rows, this is salaried workers earning below salary threshold T. Counts are monthly averages: CPS person weights (pworwgt) summed over 11 months of 2025 (outgoing rotation groups, prerelg=1) and divided by 11. The DOL (gamma) column reports expected passers using the DOL 2023 NPRM RIA Exhibit A methodology ($\sum_i p_i \cdot \mathbf{1}(earn_i < T)$); see Table 3 notes for methodology details. In the remaining columns, workers pass the duties test if the share of tasks in their occupation that are exempt exceeds a given threshold s^*, which varies across columns. In the occupation-level s^* columns, workers are assigned the share of exempt tasks associated with their occupation. In the factor model columns, task performance is simulated and exempt task shares are calculated at the individual level. Model 1 represents a scenario with some specialization and a moderate, positive within-occupation correlation between earnings and exempt work ($\lambda_G = 0.3, \lambda_X = 0.5, \rho_G = 0.3, \rho_X = 0.6$). Model 2 represents more specialization and a more strongly positive correlation ($\lambda_G = 0.3, \lambda_X = 0.7, \rho_G = 0.3, \rho_X = 0.8$). See Appendix B for factor model details and parameterization. Sample includes salaried workers with valid earnings in CPS outgoing rotation groups. Subgroups are the same as those considered by the Kantor test. Low-wage industries are those with weighted mean salaried earnings in the bottom third of major industry groups.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, DOL probability codes, task exemption classifications, and author's calculations.

Table C3: Extended State-Level Stacked DiD: Effect of Overtime Threshold Change on Worker Outcomes

	(1) Sal.≤new	(2) Sal.>new	(3) Hrly.≤new	(4) Hrly.>new	(5) Not empl.
Panel A: Salaried workers, earnings in [old, new) range					
Treat × After	-0.0850***	0.0001.	0.0309***	0.0333***	0.0207*
	(0.0188)	(0.0114)	(0.0078)	(0.0103)	(0.0121)
N	76,871	76,871	76,871	76,871	76,871
Panel B: Previously unemployed workers (hires)					
Treat × After	-0.0166***	0.0109*	-0.0250***	0.0036.	0.0270***
	(0.0033)	(0.0059)	(0.0072)	(0.0050)	(0.0095)
N	189,337	189,337	189,337	189,337	189,337

Notes: Sample includes workers observed twice in CPS outgoing rotation groups, before and after changes in state salary level test thresholds. Outcome variables are binary indicators for whether a worker has a salaried (sal) or hourly (hrly) job at or below vs above the new salary level test threshold, or is not employed. Effects are estimated using the stacked difference-in-differences analysis described in equation 1, following Quach (2024), extended to include all state-level overtime salary threshold increases through 2025 (AK, CA, CO, ME, NY, WA). Panel A: treated workers are salaried, in the state raising its threshold, with weekly earnings in [old threshold, new threshold) for that event. Panel B: treated workers are unemployed in the pre-year. Control workers in both panels are those with the same employment status in non-treatment states. Ever-treated states (AK, CA, CO, ME, NY, and WA) are excluded from the control pool for all events. Regression includes event × state and event × period FEs, as well as age, sex, race/ethnicity, and education fixed effects. Standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Current Population Survey Outgoing Rotation Groups, and author's calculations.

Table C4: Post-Quach State-Level Stacked DiD by Exemption Status

	(1) Sal.≤new	(2) Sal.>new	(3) Hrly.≤new	(4) Hrly.>new	(5) Not empl.
Treat × After (low exempt)	-0.0672***	-0.0123.	0.0346***	0.0310.	0.0138.
	(0.0255)	(0.0245)	(0.0121)	(0.0223)	(0.0163)
Treat × After × High exempt	-0.0290.	0.0406.	-0.0207*	-0.0004.	0.0094.
	(0.0227)	(0.0250)	(0.0124)	(0.0221)	(0.0103)
Implied DiD for high-exempt workers (sum of above):					
Treat × After (high exempt)	-0.0962***	0.0284***	0.0140*	0.0307***	0.0232**
	(0.0183)	(0.0096)	(0.0079)	(0.0055)	(0.0104)
N	76,871	76,871	76,871	76,871	76,871

Notes: Sample includes workers observed twice in CPS outgoing rotation groups, before and after changes in state salary level test thresholds. Outcome variables are binary indicators for whether a worker has a salaried (sal) or hourly (hrly) job at or below vs above the new salary level test threshold, or is not employed. Effects are estimated using a stacked triple difference analysis incorporating task-based exemption measures, extending the events in Quach (2024) to include all state-level overtime salary threshold increases through 2025. Treated workers are salaried, in the state raising its threshold, with weekly earnings in [old threshold, new threshold) for that event. Control workers are those with the same salary status in non-treatment states. Ever-treated states (AK, CA, CO, ME, NY, and WA) are excluded from the control pool for all events. High-exempt workers are those in occupations with more than half of tasks classified as exempt. The implied DiD for high-exempt workers is a linear combination estimated via `lincom`; its standard error accounts for covariance between the two coefficient estimates. Regression includes event × state and event × period FEs, as well as age, sex, race/ethnicity, and education fixed effects. Standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Current Population Survey Outgoing Rotation Groups, O*NET, task exemption classifications, and author's calculations.