How Do Establishment Size, Industry Size, and Minimum Wage Help Explain the Post-2015 Structural Shift in Wage Inequality Between Digital and Non-Digital Firms?

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ABSTRACT

I identify a post-2015 divergence in wage inequality between digital and non-digital firms. I then examine how establishment size, industry size, and minimum wage policies help explain this divergence. I use machine learning models and perform differences-in-differences regressions on industry-level and establishment-level data from 2007 to 2022. Industry size consistently amplifies inequality, while establishment size shows weaker effects. Neither fully explains the 2015 divergence, but industry size is a better proxy for underlying mechanisms. A minimum wage analysis between California and Nevada reveals causal effects of minimum wage on wage inequality but through different mechanisms, evidenced by diverging mean-median wage gaps and Gini coefficients.

Keywords: Wage Inequality, Digital Economy, Establishment Size, Industry Size, Minimum Wage

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I. Introduction

Over the past few decades, wage inequality in the United States has shifted, exhibiting both a long-run upward trajectory and, in certain instances, sudden "structural breaks." In this paper, I focus on one such inflection point that emerges around 2015, when wage inequality between digital and non-digital industries begins to diverge at an accelerated pace. My goal is to understand underexplored mechanisms—particularly establishment size, industry size, and minimum wage policies—that may explain why the mean-median wage gap and other inequality measures increased more sharply in these so-called "digital" industries relative to their non-digital counterparts.

This empirical investigation draws on and extends the growing body of literature that highlights the role of technological adoption, task polarization, firm heterogeneity, and industry-wide transformations in driving wage dispersion. Building on the new findings of Haltiwanger, Hyatt, and Spletzer (2024)—who show that a small set of "dominant" four-digit NAICS industries, including both high-tech and low-wage service sectors, accounts for most of the rise in between-industry earnings inequality—this paper focuses on digital industries, broadly defined, to analyze how size (both at the establishment and industry level) interacts with state-level policy shifts like the minimum wage. Event-study approaches and differences-in-differences analyses across states (for instance, comparing California and Nevada) are employed to tease out the extent to which regulatory policies, technology shocks, or broader industry restructuring shaped the post-2015 surge in inequality.

II. Literature Review

A recent finding in the inequality literature is that a small group of high-paying and low-paying industries has come to dominate the rise in wage dispersion, particularly in the United States. In "Rising Top, Falling Bottom" (Haltiwanger, Hyatt, and Spletzer, 2024), the authors show that while within-firm wage dispersion remains significant, the bulk of the increase in overall inequality between 1996 and 2018 is driven by between-industry variation. Notably, ten percent of four-digit NAICS industries—those that experienced major restructuring or rapid technological advances—account for most of this rise. High-paying industries see both wage and employment growth, while low-paying industries see employment growth despite stagnant or declining wages. This industry-level dominance is related to long-standing research on firm or industry "superstars," in which a handful of large, successful firms or sectors increasingly capture both market share and wage growth (Autor et al. 2020).

Technological change has long been recognized as a key driver of wage dispersion through its complex interactions with skill-biased innovation, labor-substituting automation, and new organizational structures (Acemoglu and Autor 2011). Acemoglu and Restrepo (2022) show that new tasks generated by automation tend to polarize labor markets, especially when the technological frontier moves rapidly. Digital industries, such as information, finance, and professional/technical services, are often early adopters of cutting-edge technologies—ranging from cloud computing to AI-driven platforms—facilitating productivity gains that disproportionately benefit high-skilled workers. At the same time, these digital firms often outsource or automate mid- and low-skilled tasks, thereby generating wage polarization at both ends of the skill distribution (Autor, Katz, and Kearney 2006; Goos and Manning 2007).

Moreover, the concept of "digitalization" itself can extend beyond pure tech sectors. Guellec and Paunov (2017) point out that digital innovation increasingly permeates all sectors of the economy, altering business models and raising the skill premium. Finance, for instance, relies heavily on digital tools (e.g., fintech platforms, algorithmic trading), while many professional and technical services revolve around software-driven solutions. This breadth of digital penetration—accompanied by substantial intangible investments and winner-take-most market structures—reinforces a "superstar" dynamic in wage and profitability outcomes.

On the firm side, Bloom et al. (2018) demonstrate that the historically large-firm wage premium has eroded, especially for lower-skilled positions, even as some large employers remain influential. Song et al. (2019) highlight how between-firm differences—including the sorting of high-wage workers into certain firms—play a major role in rising wage inequality, a pattern consistent with "superstar" or "mega firm" dynamics in some high-tech industries. "Superstar" firms often pay more to top-skilled workers, thereby amplifying between-firm and between-industry inequality. However, recent evidence indicates that the large-firm wage premium continues to dissipate in many sectors, in part due to outsourcing strategies and a shift toward contract-based gig or platform work (Collier et al. 2017). Haltiwanger, Hyatt, and Spletzer (2024) add nuance to this narrative, showing that while some large, high-tech firms drive top-end wage growth, certain retail or hospitality companies increase employment in low-wage jobs, pulling down average wages at the lower tail.

Research into wage polarization must also account for labor market institutions, particularly minimum wage policies. Studies document that increases in minimum wages can compress wage distributions at the lower tail but may also have unintended spillover effects, such as reduced employment in certain sectors or upward shifts in the mid-range of the distribution (Allegretto et al. 2017). In the post-2015 context, especially in states like California that enact stepwise minimum wage hikes, the interplay between regulatory changes and technological adoption becomes salient: while policy can raise the wage floor, digital automation or large-establishment reorganization might blunt those gains by reallocating tasks or reshaping production processes. My comparison of California and Nevada—two neighboring states with contrasting minimum wage paths—draws directly on this line of work, extending our understanding of how policy divergence either mitigates or magnifies inequality.

A complementary stream of research underscores that the wage distribution is increasingly tied to the nature of tasks or occupations rather than broad skill categories alone. Autor, Katz, and Kearney (2006, 2008) document how routine-biased technological change displaces mid-wage, routine-intensive tasks, fueling growth in both high-wage cognitive jobs and low-wage manual-service ones. While these analyses initially centered on broad “routine” versus “non-routine” occupations, subsequent work (Autor et al. 2020; Haltiwanger, Hyatt, and Spletzer 2024) reveals that occupational polarization often manifests at the industry level, with specific clusters of industries absorbing low-skilled, low-wage labor and others employing a higher share of professional and technical occupations. This dovetails with the emerging patterns in digital sectors, where high-paying business or STEM occupations concentrate.

The literature indicates that macroeconomic trends such as digitalization, task automation, and globalization reshape labor markets primarily through the evolving structures and strategies of a relatively small set of industries. These industries often exhibit large or growing establishment size, high degrees of market concentration, and rapid technological change—and their wage practices spill over into the broader economy, especially when regulatory policies like minimum wages intersect with firm reorganizations. The novel contribution of this study is to pinpoint a structural break around 2015 in the digital versus non-digital wage inequality gap and to rigorously analyze whether establishment and industry size, combined with minimum wage changes, account for this abrupt divergence. By employing differences-in-differences and machine learning techniques (ML TODO Next quarter) on state-industry-level data, this paper aims to shed new light on the multifaceted drivers of wage inequality in an era where digital transformation and policy experimentation often move in parallel.

III. Background

After 2000, I observe two major forces reshaping the American labor market in ways that bear directly on wage inequality: a sweeping digital transformation of industries and state-level labor market policies that include varied minimum wage legislation. These forces intensify around the mid-2010s when wage gaps between digital and non-digital firms widen faster than in prior years. Below, I outline the key developments that motivate my focus on a post-2015 structural shift in United States wage inequality.

I use the term “digital industries” to describe sectors, including information, finance, and professional/scientific/technical services, where technology adoption heavily influences production and labor demand. I also track “digital intensity” using measures from the Brookings Institution, as described in the data section. By the early 2010s, advances such as cloud computing, data analytics, and artificial intelligence spurred notable wage growth for highly skilled roles. At the same time, digitalization has fostered the rise of platform-based business models that magnify returns for certain “superstar” firms. The combination of rapid technological change and intangible capital investments positioned these digital sectors to outpace more traditional industries in both productivity and pay levels.

As digital firms grow, large establishments (with thousands of employees) become increasingly common. Some of these large employers continue offering premium wages, particularly for top-skilled workers, thereby driving up average pay in their industries. In other sectors, particularly retail and hospitality, large chains seek scale economies and keep wages comparatively low, pushing their average pay toward the bottom of the overall distribution. This twin phenomenon—rapid wage gains in high-tech establishments and stable or lagging wages in service-heavy behemoths—appears to have amplified inter-industry inequality around 2015.

Furthermore, around 2014, several states continued with multi-year plans to raise the minimum wage. For example, California passed legislation to incrementally increase the minimum wage from $9 in 2014 to $15 by 2022, while other neighboring states followed slower or smaller trajectories. These differing policies create quasi-natural experiments in which the wage floor may accelerate automation in some industries or compress pay in others. By contrasting high-minimum-wage states and more moderate states, I isolate whether policy environments contribute to the evolving wage gap between digital and non-digital firms.

Finally, I treat 2015 as a logical breakpoint. The long recovery from the Great Recession restored aggregate employment, but wage growth remained uneven across regions and sectors. Digital-oriented businesses capitalized on cheap capital and the expanding consumer base for online platforms, while many low-wage or mid-skill roles had not fully rebounded. By the mid-2010s, these factors coalesced into a stark divergence: digital industries began posting outsize wage gains, whereas large segments of the service sector lagged behind.

Taken together, these developments prime my empirical analysis for a post-2015 structural shift in wage inequality. I examine whether the observed divergence is most attributable to the expansion of digital industries, the ascendancy (or wage practices) of large establishments, or the impact of policy changes such as minimum wage hikes—and whether interactions among these factors help explain the widening wage gap that emerged after 2015.

IV. Data

I construct a comprehensive panel dataset for wage statistics by industry and state for 51 states from 2007 to 2022. The data come from the U.S. Census Bureau's Statistics of U.S. Businesses (SUSB), the Bureau of Labor Statistics, the Department of Labor, the Integrated Public Use Microdata Series (IPUMS) USA, Federal Communications Commission (FCC) Form 477 broadband data, and the Brookings Institution. In total, the sample contains 14,414 observations spanning 19 industries and 963 state-industry pairs, with an average of about 15 years of coverage per state-industry combination (see Table 1 in the Appendix).

Each observation records the number of workers, mean wage, median wage, wage bill, a measure of wage inequality, and a measure of "digital intensity" from the Brookings Institution, interpolated linearly. The Brookings Institution combines knowledge of computers and the importance of interacting with computers from an Occupational Information Network survey from the U.S. Department of Labor. I primarily use the mean–median wage difference (available through 2022) as my inequality metric; for some robustness checks, I use the Gini coefficient (available through 2021). The dataset is 98.9% balanced, with 99.2% data completeness and fewer than 7% missing values (which I drop). I also flag, but do not remove, suspicious entries (e.g., mean wage below median wage). No cases of zero or negative wages are observed.

A few descriptive patterns emerge. Across the full dataset, the average mean wage is about $47,483, whereas the median wage is about $35,000, implying an average mean–median wage gap ("wage inequality") of roughly $10,700. This gap varies substantially: the minimum is about $92,740 and the maximum is $160,222. Regionally, the South accounts for the largest fraction of observations at 33.4%, followed by the West (25.5%), the Midwest (23.4%), and the Northeast (17.7%).

I divide the sample into three phases—pre-2015, post-2015, and the COVID-19 era—based on evidence of a structural shift around 2015 and the labor market disruptions starting in 2020. The dataset thus allows for longitudinal analysis of both wage levels and wage inequality across nearly all U.S. states and a rich array of industries.

Finally, I merge additional data on state-level minimum wages through 2020 and on broadband deployment (2015–2022), enabling supplementary causal analyses (e.g., effects of policy changes, tech adoption, or cross-border variations). This yields a robust and detailed dataset for understanding how wage inequality evolves when industries expand or contract, large versus small establishments shift employment, and different states implement divergent wage and technology policies.

V. Empirical Method

I employ a triple-differences-in-differences (DDD) design to quantify the effects of the 2015 transformation on wage inequality, focusing on both establishment size (2007–2021) and industry size (2007–2022). I primarily use the Gini coefficient as the measure of inequality. Digital industries include information, finance and insurance, and professional, scientific, and technical services, while non-digital industries encompass the remaining sixteen sectors (e.g., manufacturing, agriculture, mining). This approach allows me to capture any post-2015 divergence in wage inequality between digital and non-digital industries and assess whether entity size (establishment or industry) moderates these differences.

The equation I will run is the following:

$$WI_{it} = \beta_0 + \beta_1 Size_{it} + \beta_2(Digital\ x\ Post2015)_{it} + \beta_3(Size\ x\ Digital\ x\ Post2015)_{it} + \alpha_{We} + \gamma_t + \varepsilon_{it}$$

where WI_it denotes wage inequality (Gini coefficient), Size_it is either establishment or industry size, Digital_it is an indicator for digital industries, Post2015_it is an indicator for the post-2015 period, alpha_i and gamma_t are entity and time fixed effects, and epsilon_it is the error term.

Digital industries include information, finance and insurance, and professional, scientific, and technical services. Non-digital industries include the sixteen others, primarily manufacturing, agriculture, forestry, fishing, and hunting, and mining, quarrying, and oil and gas extraction. I add the third term in the DDD to examine whether the effect of the 2015 transformation differs by entity size, adding a layer of heterogeneity. I run this regression on the mean-median wage difference as well.

Importantly, I adjust this regression to include within-industry variation with Brookings Institution "digital intensity." I keep the previous regression in this section because the Brookings Institution data ends in 2016, so later years take the 2016 value. The additional regression is the following:

$$WI_{it} = \beta_0 + \beta_1 Size_{it} + \beta_2 DigitalIntensity_{it} + \beta_3 Post2015_t + \beta_4(DigitalIntensity_{it}\ x\ Post2015_t)$$
$$+ \beta_5(Size_{it}\ x\ DigitalIntensity_{it}\ x\ Post2015_t) + \alpha_i + \gamma_t + \varepsilon_{it}$$

where DigitalIntensity is the continuous Brookings Institution variable.

One state-level example is considered. The question I pose on a small scale is how does minimum wage affect wage inequality? California and Nevada are selected for a minimum wage differences-in-differences analysis from 2007 to 2019 because they border and have a clear minimum wage divergence. I exclude 2020-2021 because of COVID-19 volatility, although it slightly strengthens statistical significance. The regression specification is as follows:

$$WI_{it} = \beta_0 + \beta_1 State_s + \beta_2 Post2015_t + \beta_3 (State_s \, x \, Post2015_t) + \varepsilon_{st}$$

I run the analysis using the mean-median wage difference and the Gini coefficient. In addition, I assess parallel trends from 2007 to 2013 and run a placebo study, exclude years, run different time windows, and run a comprehensive event study. I also run this analysis on different states with different specifications.

VI. Results

The DDD analysis indicates that digital industries did not experience significant increases in wage inequality post-2015 (Digital × Post-2015, coefficient = +0.0117, p = 0.1285) when using establishment size. Larger establishments in digital industries show no significant moderation of inequality (Size × Digital × Post-2015, coefficient = +7.028e-05, p = 0.2462). These results suggest a limited role of the 2015 structural break in driving wage inequality at the establishment level.

Using industry size, however, the DDD analysis indicates that digital industries experienced significant increases in wage inequality post-2015 (Digital × Post-2015, coefficient = +0.0165, p = 0.0044), confirming a structural shift. Larger industries within the digital sector slightly mitigated this increase (Size × Digital × Post-2015, coefficient = -3.604e-06, p = 0.0556). Thus, industry size provides a clearer picture of the post-2015 structural change than establishment size, highlighting the distinct role of digital sectors in driving wage inequality.

The within-industry regression confirms that, for smaller industries, higher digital intensity is associated with slightly lower wage inequality overall (digital_intensity coefficient = −0.0007, $p<0.01$), and that effect becomes more negative post‑2015 (intensity × post coefficient = −0.0014, $p=0.002$). However, in large industries, the positive triple interaction (size × intensity × post = +0.0005, $p<0.001$) more than outweighs that negative component, implying that big, highly digital industries see a rise in the wage gap after 2015. This finding comports with "winner‑take‑most" or "superstar" firm dynamics in large, tech‑oriented segments, whereas smaller digital industries appear to exhibit a modest compression of wages.

A mild pre‑trend emerges around three years before 2015 (intensity_x_t−3 $p=0.023$; size_x_intensity_x_t−3 $p=0.030$), suggesting that big/digital segments may have begun diverging slightly before the chosen break. Nevertheless, most pre‑trend coefficients are insignificant, indicating that the parallel‑trends assumption broadly holds—albeit with a small caveat near 2012.

I find two distinct effects of minimum wage increases on wage inequality. The mean-median wage gap shows a significant increase of $3,238 ($p=0.010$) in the base specification. This effect varies across time windows: longer periods show significant increases (2007-2015: +$3,198, $p=0.044$; 2014-2019: +$2,865, $p<0.001$), while shorter windows show smaller, insignificant effects (2012-2016: +$1,718, $p=0.388$; 2011-2017: +$1,358, $p=0.399$). However, several specification checks raise concerns about this finding. Pre-trend analysis reveals divergent trajectories in the focused window, with California showing annual increases of

$1,079 compared to Nevada's $3,255. Placebo tests produce significant effects in three of four false treatment years (2012: +$3,224, p=0.016; 2013: +$2,812, p=0.027; 2015: +$2,674, p=0.037). Additionally, the control state exhibits volatility, with mean-median gaps fluctuating from $7,614 in 2011 to $11,430 in 2013 before declining to $8,311 in 2014.

Conversely, the Gini coefficient analysis indicates a significant decrease of 0.0315 (p=0.048) following minimum wage increases. There are no significant placebo tests, consistent effects across time windows, and better pre-trend alignment between treatment and control states.

For establishment size results, see Table 2 in the appendix. For industry size results, see Table 3 in the appendix. For industry size results that account for within-industry variation, see Table 4 in the appendix.

VII. Conclusion

The relationships between establishment size, industry size, and wage inequality are nuanced. I find establishment size is weakly related to median wages and positively associated with wage inequality but with low explanatory power. Industry size plays a more consistent and significant role in wage inequality, with larger industries generally increasing inequality but still with significant industry and establishment heterogeneity. Non-linear patterns in both establishment and industry size suggest diminishing returns to inequality growth, potentially due to structural or regulatory constraints.

Industry-specific dynamics are incredibly important. For example, retail amplifies wage inequality, while finance and insurance mitigate it. I also find pronounced regional differences (e.g., between the Midwest and Northeast), and I find that post-2015 shifts suggest macroeconomic structural changes influenced size-inequality relationships, particularly in digital industries at the industry level, while establishment-level effects were minimal.

Results do not indicate that industry size was primarily responsible for the increase in wage inequality between digital and non-digital industries but rather that it serves as a meaningful proxy for more complex structural dynamics. This should be followed by a machine learning heterogeneity analysis. I propose future research to understand the mechanisms driving the post-2015 structural change.

The minimum wage analysis suggests that minimum wage increases have complex effects on wage inequality, operating through different channels in the wage distribution, and provides a causal result to strengthen this paper's contribution to the research community. Reductions in the Gini coefficient suggest compression within categories, but simultaneous increases in the mean-median gap (although less robust) suggest growing overall wage dispersion. This contradiction likely reflects the gradual, cumulative impact of California's sequential minimum wage increases from $8 in 2013 to $12 in 2019 rather than an immediate policy effect. The divergent results between the two inequality measures highlight the importance of considering multiple metrics when evaluating distributional policy impacts. Future research might explore whether similar patterns emerge in other state pairs and investigate the channels through which minimum wages simultaneously compress within-category wages while potentially expanding overall wage dispersion.

I implement checks to confirm the robustness of all findings—parallel trends assessment, placebo tests, and alternative inequality measures—yet these results still have their limitations. Nevada exhibited meaningful volatility in the minimum wage, making shorter time periods statistically insignificant. Mechanism proxies are suggestive at best. Data, although comprehensive, could include a longer time horizon to better understand the impacts of COVID-19. Furthermore, the DDD has a few key limitations: (i) selection: firms choose to be digital, (ii) treatment: "digital transformation" is gradual, and (iii) spillovers likely exist between firms. Even when adjusting the DDD for within-industry variation, data is limited to 2016.

One note about this study's findings is that although wage inequality increased post-2015 in digital industries (overall divergence in wage via mean-median wage and smaller-scale divergence via the Gini coefficient), I do not make judgment claims about wage inequality.

Reiterating the contributions of this study, I provide a comprehensive dataset with statistics on industry size, establishment size, minimum wage, 5G implementation (in 2019), and "digital intensity" for future study. I find causal evidence that the minimum wage may have increased the mean-median wage difference while simultaneously reducing the Gini coefficient in California and Nevada from 2014 to 2019, and I identify a significant reversal in wage variation between digital and non-digital firms post-2015, indicating a unique structural shift that is not present in years from 2007 to 2015. Future research is necessary to better understand the mechanisms underlying the 2015 structural change.

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Appendix

Table 1: Summary Statistics

Metric	Value
Total Observations	14,414
Unique States	51
Unique Industries	19
State-Industry Pairs	963
Years Covered	2007-2021

Large Establishment Intensity	Median Wage	Mean Wage	Wage Inequality	Wage Inequality Ratio
Count	14,414	14,414	14,414	14,414
Mean	0	36,769	47,483	10,714
Std. Dev	0	18,683	22,339	8,258
25%	0	22,000	30,650	5,933
Median	0	35,000	44,141	9,082
75%	0	46,000	59,211	13,942
Min	0	60	3,000	-92,740
Max	1	328,000	270,222	160,222

Observations	Share	States	Industries	Mean Size	Median Size
Midwest	3368	23.4%	12	19	0
Northeast	2555	17.7%	9	19	0
South	4810	33.4%	17	19	0
West	3681	25.5%	13	19	0

Period	Years	Observations	Share	Mean Workers	Mean Wage	Median Wage

					Inequality	Inequality
Pre-2015	2007-2014	7,684	53.5%	0	9,510	8,086
Post-2015	2015-2019	4,807	33.3%	0	11,728	10,049
COVID Period	2020-2021	1,923	13.3%	0	12,988	11,329

Table 2: Establishment DDD Results

	Parameter	Std. Error	P-value
Weighted Establishment	0.0012	0.0003	0.0001
Size * Digital * Pre-2015	−9.0016	0.0003	0.0000
Size * Post-2015	−0.0001	5.588	0.0461
Digital * Post-2015	0.0117	0.0077	0.1285
Size * Digital * Post-2015	7.028	6.061	0.2462

Table 3: Industry DDD

	Parameter	Std. Error	P-value
Workers	0.1722	0.0035	0.0000
Size * Digital * Pre-2015	7.449	4.156	0.0731
Size * Post-2015	8.879	1.428	0.0000
Digital * Post-2015	0.0165	0.0058	0.0044
Size * Digital * Post-2015	−3.604	1.883	0.0556

Table 4: Continuous Digital Intensity Industry DDD

Parameter	Estimate	Std. Error	P-value
Constant	0.1563	0.0273	0.0000
log_workers	-0.0065	0.0044	0.1390
digital_intensity	-0.0007	0.0001	0.0000
intensity_x_post	-0.0014	0.0004	0.0018
size_x_intensity_x_post	0.0005	6.85e-05	0.0000

Figure 5: Mean-Median Wage Gap Visualization in Digital and Non-Digital Industries Pre- and Post-2015

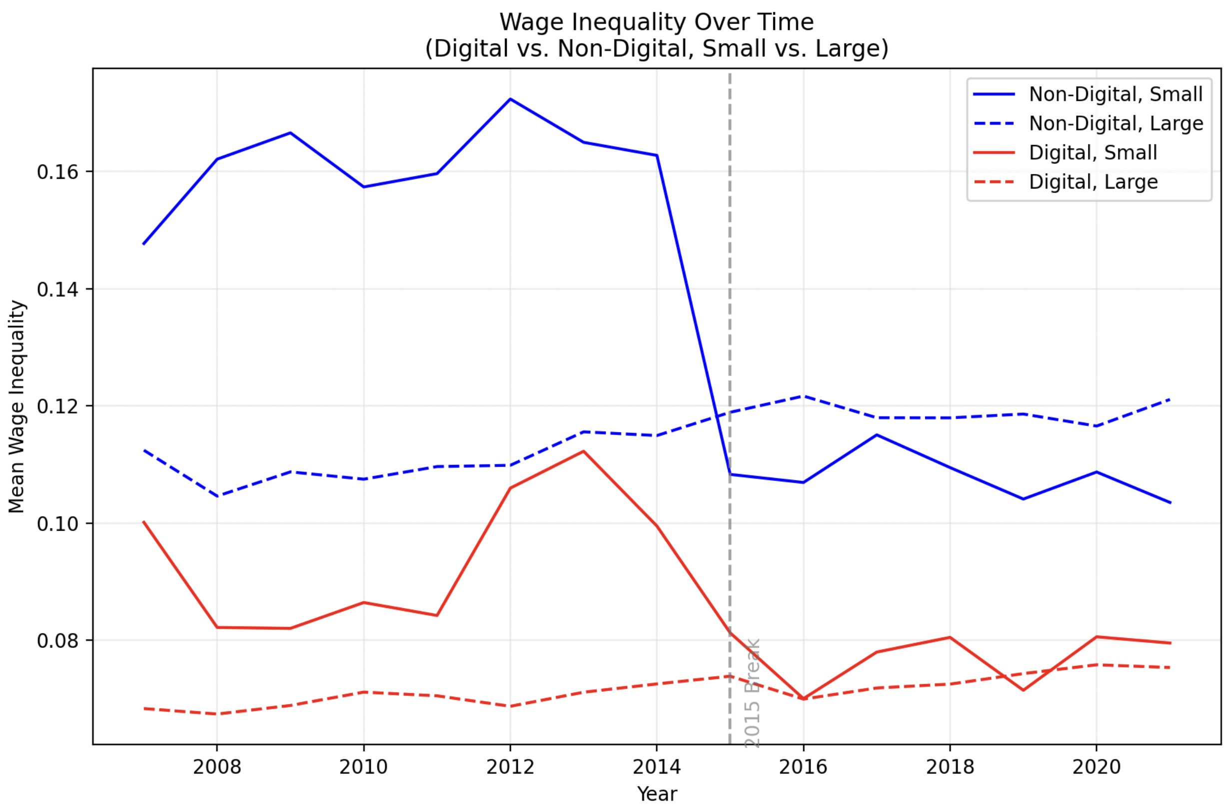

Figure 6: Mean-Median Wage Gap in California and Nevada