

# Extended Abstract: The Relationship Between the "Norm to Work" and Labor Market Outcomes

## *PRELIMINARY RESULTS*

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### **Abstract**

This project explores how work norms may shape the labor market. Media narratives and existing research suggest such norms are important drivers of worker behavior and, ultimately, macroeconomic outcomes like labor supply and wages, but this idea has not been tested empirically due to the difficulty of measuring norms. I construct a novel measure of work norms using unstructured text data from Twitter, combined with a custom-built machine learning model to label the text. I then use this measure to examine the relationship between work norms and labor market outcomes such as labor force participation, employment, and wages.

## **1 Introduction**

The past decade has seen a surge of interest among economists in the extent to which social norms may shape labor market outcomes.<sup>1</sup> Although much of this work is focused on gender norms, recent labor market upheavals in the wake of Covid-19 have also highlighted the potential importance of broader social norms and attitudes regarding work, with many commentators claiming that a pandemic-induced re-evaluation of the importance of work has led to more quits, higher wages, and a resurgence in worker power (e.g., Hirsch 2021; Krugman 2021; Sull, Sull, and Zweig 2022). While there is some evidence of decreased willingness to work and increased worker power in the form of unionization, this narrative has proven difficult to test empirically (Faberman, Mueller, and Şahin 2022; Kinder and Stateler 2022), in large part because social norms are so challenging to quantify. The big-picture question remains: to what extent does the "norm to work"—i.e., the social norm that working-age adults should be employed—influence worker behavior and, ultimately, macro-level outcomes such as employment and wages?

Existing research has established that social norms are powerful drivers of human behavior (e.g., Coleman 2018; Elster 1989; McAdams 1997), and this appears to be especially true in the labor market. Unemployment carries heavy psychological costs even after controlling for financial duress (Blanchflower and Oswald 2004; Brand 2015; Jahoda 1988). Research has also shown that these psychosocial costs are determined in part by unemployment rates or the prevailing social norms in one's community (often treated as equivalent in earlier work) (Powdthavee 2007; Stavrova, Schlösser, and Fetchenhauer 2011). Unemployed people tend to be unhappier in areas with stronger work norms, and there is some evidence suggesting that the unemployed expend more effort on job search when

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1. Recent examples of papers in this area include, but are certainly not limited to: Bertrand et al. 2016; Binzel and Carvalho 2017; Breza, Kaur, and Krishnaswamy 2019; Bursztyn, Fujiwara, and Pallais 2017; Bursztyn, González, and Yanagizawa-Drott 2020; Dube, Naidu, and Reich 2022, Fortin 2015; Jayachandran 2021.

employment norms are stronger (Chadi 2014; Clark 2003; Eugster et al. 2017; Stutzer and Lalive 2004). It also seems plausible that employed people take greater pains to avoid unemployment in locations with a stronger NTW, though there is currently no empirical evidence of this. Taken together, then, the NTW has a potentially large impact on job search and labor supply behavior.

While the literature has established a clear link between the NTW and the well-being and behavior of unemployed people, no existing research has moved beyond these individual-level, direct effects to study the potential aggregate-level impacts of work norms. Additionally, prior work has been limited by the difficulty of measuring the NTW. The papers referenced above largely rely on survey data, which tends to be irregularly intervalled and geographically coarse, or else simply use measures of local or network-level unemployment as a proxy for employment norms (so-called "descriptive" norms). Creative exceptions include Stutzer and Lalive 2004 and Eugster et al. 2017, which exploit region-level vote shares from a Swiss referendum on unemployment benefits and a language border that separates cultures (but not labor markets), respectively. However, such solutions are unique and highly context-specific. This paper aims to address these gaps.

This paper offers preliminary evidence of a relationship between the social norm to work ("NTW") and labor supply, using a novel, social media-based measure of norms. This is the first empirical evidence documenting an effect of work norms on aggregate labor market outcomes. The initial results are noisy, but suggest a positive relationship between the NTW and the labor supply of young men. This aligns with theoretical predictions as well as demographic features of the source data for the NTW measure.

The NTW measure developed for this project is unique in its scope and geographic granularity, and thus may prove useful to economists studying a broad array of questions exploring the impact of norms in the labor market. More broadly, the methodology employed to create the measure may be easily generalized to other norms, providing researchers with a new tool for quantifying social norms in different contexts.

## 2 Measuring the Norm to Work

The norms measures used in this paper are based on data from Twitter, labeled using a custom-trained text classification model. Figure 1 presents an outline of the measure construction workflow, which is described in more detail below.

### Tweet sample

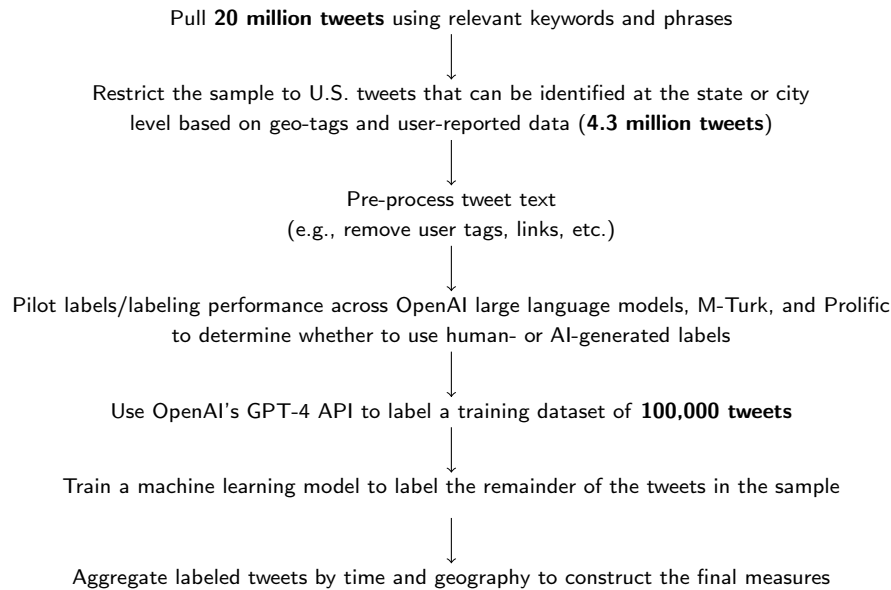
The NTW measures in this paper are based on a sample of roughly 20 million tweets collected through Twitter's Academic API.<sup>2</sup> The sample was selected using keyword searches intended to filter for tweets relating to the norm to work and attitudes towards employment and unemployment<sup>3</sup>. The sample begins in 2011—the year when Twitter reached 100 million users—and ends in November 2022, when the tweets were collected (Meyer 2019). After dropping tweets that were from outside the U.S. or missing geographic data (based on user-reported locations or geo-tags), the final sample

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2. The Academic API, along with all other affordable tiers of Twitter API access, was discontinued in 2022 following Elon Musk's acquisition of the platform.

3. While some searches were based on single keywords (e.g., for "unemployment") many topic words (e.g., "work") were too vague to yield a reasonable proportion of relevant tweets. Therefore, I employed many multi-word searches intended to triangulate beliefs and attitudes towards work and employment (e.g., a keyphrase search for tweets containing ("work" OR "job") AND "lazy", meant to roughly capture sentiments along the lines of "people who don't work (or have a job) are lazy").

Figure 1: Outline of the measure construction workflow



consists of about 4.3 million tweets<sup>4</sup>.

## Tweet labeling

I employ a supervised machine learning approach to perform multi-class label classification on each tweet in the sample. As there is little concrete guidance regarding the exact language that best characterizes the NTW, I include several different (exclusive) category labels capturing different facets of work norms, as follows:

1. Anti-work
2. Norm to work
3. Pro-workers' rights
4. Unemployment stigma
5. Not applicable

The final label captures relevance, as many of the tweets in the sample are simply off-topic. The labels were chosen to distinguish between positive versus negative framings of the social norm to work, as well as positive versus negative framings of the opposing (anti-work) attitudes. In practice, the labels appear to capture meaningfully different concepts. Upon inspection of the labels chosen by workers on MTurk or Prolific, "norm to work" and "anti-work" seem to be interpreted more broadly or abstractly, while "pro-workers' rights" or "unemployment stigma" tend to be chosen for tweets containing more concrete and specific language around (e.g., advocating for better working conditions or criticizing unemployment benefits).

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4. The Twitter API does not permit filtering based on users' self-reported locations (the primary source of geographical data), so many of the collected tweets had to be dropped from the sample ex-post.

Supervised machine learning requires a pre-existing set of correctly-labeled data to train a model—typically a dataset that has been manually labeled by humans. After conducting a pilot study comparing labels for 700 tweets generated by workers on M-Turk and Prolific to labels chosen by OpenAI’s GPT-3.5 and GPT-4 models, I instead opted to use GPT-4 to label the training dataset, as the data quality appeared to be similar across these sources. I used GPT-4 to label a training dataset of 100,000 tweets, with each tweet classified into one of the categories listed above. I then used this set of 100,000 labeled tweets to train a machine learning model<sup>5</sup> for this multi-class labeling task, which generated predicted labels for the remainder of the tweets in the sample.

The details and performance of the preliminary tweet classification model are summarized in Tables 1 and 2 below. The overall accuracy of the multi-class classification on hold-out data is ~ 62%, though accuracy considering each label individually (binary classification) is higher. This level of accuracy is in line with the accuracy of text classification models used in similar contexts<sup>6</sup>, but introduces a significant amount of noise into the final NTW measures.

Table 1: Model summary

Layer (type)	Output shape	Parameters
embedding 1 (Embedding)	(None, 67, 200)	10000000
lstm 1 (LSTM)	(None, 64)	67840
dense 1 (Dense)	(None, 64)	4160
dense 2 (Dense)	(None, 5)	325

Table 2: Model performance

Model	Accuracy	Precision	Recall
Multi-class classification (all labels simultaneously) (used for preliminary measure)	62%	71%	51%
Binary label classification: "not applicable"	78%	78%	67%
Binary label classification: "anti-work"	85%	60%	38%
Binary label classification: "norm to work"	80%	70%	59%
Binary label classification: "pro workers’ rights"	93%	63%	33%
Binary label classification: "unemployment stigma"	95%	63%	42%

This process resulted in a sample of about 4.3 million tweets, each classified into one of the categories listed above.

### Preliminary NTW measures

The labeled tweets are aggregated by time and geography to create four NTW measures (corresponding to categories 1-4 listed in the previous section). Each measure is adjusted for the volume of *relevant*

5. The machine learning model used for labeling the tweets in this sample was built using the Keras and Tensorflow packages in Python. It is a convolutional neural network model trained to conduct multi-class text classification. Convolutional neural networks are generally considered the gold standard for classification tasks with high-dimensional, unstructured data (such as tweets), as their multi-layer and flexible structure allows for highly complex data representations. Specifically, the models used in this paper are recurrent neural network (RNN) models that include long short-term memory ("LSTM") layers. RNNs are ideal for sequential data (such as text data), as they allow the model to have "memory" of data from earlier in a sequence of elements (essentially, state-dependence).

6. E.g., text classification models achieved accuracy of about 70% in Adams-Prassl, Barbanchon, and Marcato 2022, 74%-85% in Lassébie et al. 2021, and 54%-97.5% in Osnabrügge, Ash, and Morelli 2023.

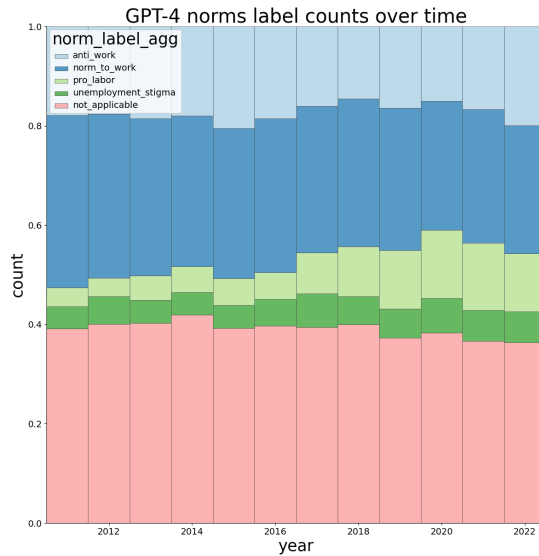
tweets in a given area at time  $t$ . The measure for each label is constructed as follows:

$$NTW_{irt} = \frac{\sum_{\text{tweet} \in \text{tweets}_{rt}} \text{label } i}{\sum_{\text{tweet} \in \text{tweets}_{rt}} \text{relevance label}}$$

Where  $r$  denotes region (with measures constructed at both the U.S. state and metro-area level),  $t$  denotes time (year), and  $i$  denotes the label being used (ranging from 1-4). Measures were constructed for all 50 states and the top 50 largest cities by population. Recall that all labels are binary, so this is equivalent to dividing the count of positive (label=1) tweets by the count of relevant (i.e., not categorized as "Not applicable") tweets for each label.

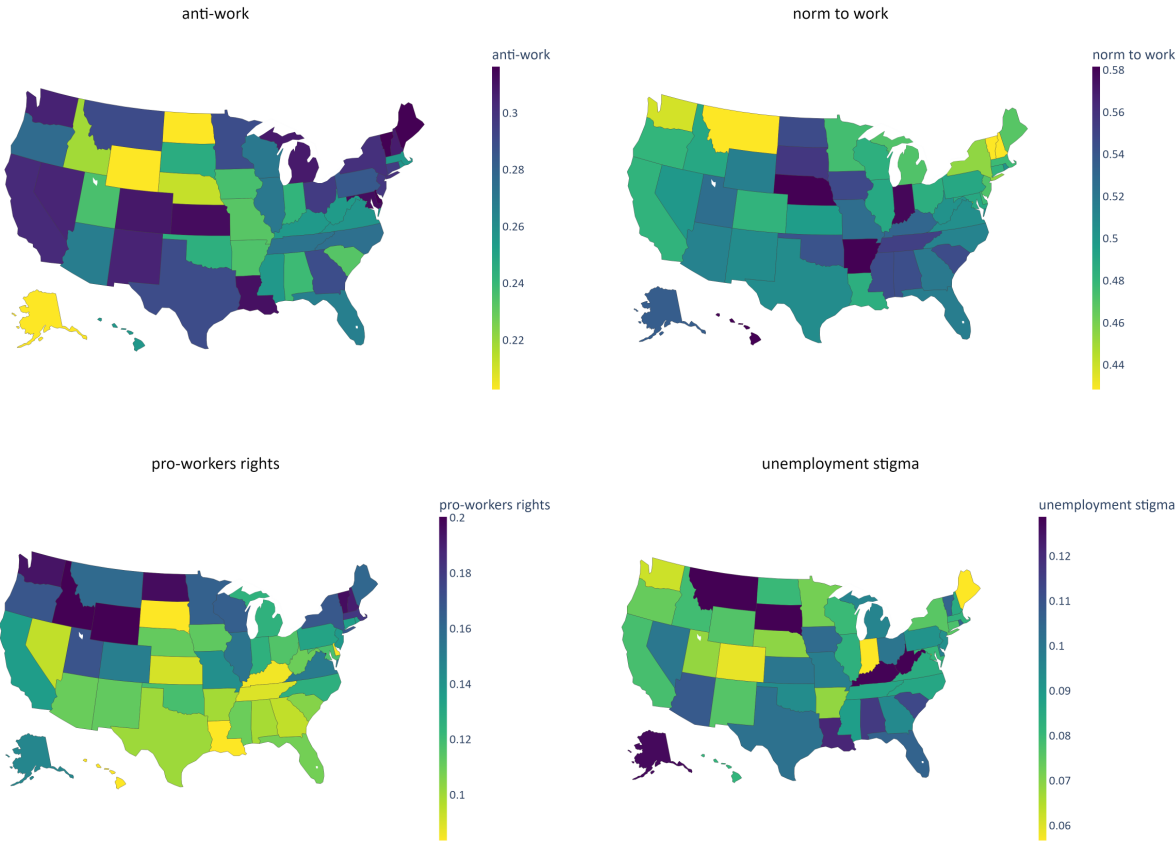
While I examined results using alternative denominators (population and gross tweet volume), adjusting for relevant tweet volume is theoretically the most robust approach. Area population does not account for variation in the amount people tweet in different areas at different times if this is not directly proportional to population. Adjusting for gross tweet volume solves this issue, but is sensitive to changes in popular interest in work-related discussions. For example, if people become more interested in discussing unemployment policy from one year to the next, but gross tweet volume remains unchanged, the NTW could look artificially higher simply because there are more relevant tweets in the latter sample (both supporting and opposing the NTW). Indeed, the gross volume-adjusted and relevant volume-adjusted measures are highly correlated (typically >95%) within years, but produce different time trends. For the reasons stated above, this paper focuses on results using the relevant volume-adjusted measures.

Figure 2: Label shares by year



As shown in Figure 2, the share of tweets expressing a "norm to work" attitude has been slowly declining since 2011, while the share of tweets expressing "pro-workers' rights" has grown over the sample period. Interestingly, there was not a dramatic shift in label shares post-Covid, suggesting that worker dissatisfaction may have been steadily building leading up to the pandemic, with Covid serving as a catalyst for discussion and change.

Figure 3: Preliminary norm levels by state (2011-2022 average)



Levels of each preliminary norm measure by state are shown in Figure 3, aggregated over all of the sample years. The level of "anti-work" sentiment by state appears somewhat noisy, but is generally consistent with what one might expect based on media narratives (e.g., stronger anti-work sentiment on the coasts, weaker in the South). The level of "norm to work" sentiment is roughly inverse to the level of "anti-work" attitudes (e.g., stronger in the South and midwest), as we should expect conceptually. Note that this is not by construction, as each tweet could be sorted into one of five possible categories. Northeastern and upper midwestern states have the highest levels of "pro-workers' rights" attitudes, consistent with historical union strongholds, while "unemployment stigma" levels approximately invert this pattern.

### 3 Results

Using the preliminary norms measures described above, I examine the empirical relationship between work norms and labor supply (as measured by labor force participation and employment) and wages. Data for the individual-level labor market outcomes used in the analysis—labor force status, employment, unemployment duration, and wage data—come from the Census Bureau's Annual Social and Economic Supplement (ASEC) of the Current Population Survey for years 2011-2019. The sample is restricted to civilian (non-military) adults aged 25-65.

Preliminary results are based on the time period from 2011-2019. While the Covid-19 pandemic presents a potentially interesting shock to work norms, it also impacted the labor market in a number of other ways, both directly and indirectly, making any interpretation of post-Covid results inherently challenging. I hope to explicitly address the impact of Covid-19 on the NTW, and possible implications for labor market dynamics post-Covid, in future iterations of this project.

All analyses employ two-way fixed effects to control for unobserved heterogeneity due to year and time-invariant geographical characteristics. However, this specification is not robust to simultaneity, an obvious concern in this setting. Therefore, the current results should be interpreted with caution—in particular, it is not currently possible to say anything definitive about the direction of causality.

The observed relationships between norms and labor supply are broadly consistent with theoretical predictions, noting however that not all results are significant at conventional levels. In particular, as shown in Tables 3 and 4, there is a strong and significant negative relationship between "anti-work" attitudes and labor force participation and employment, and a strong positive relationship between NTW and these outcomes. Labor supply results for the "pro-workers rights" and "unemployment stigma" measures are directionally consistent but imprecisely estimated. This is not surprising, as these labels were relatively rare in the training data, and ML models tend to struggle with low-incidence labels, meaning that these measures are likely noisier.

Wage results are imprecisely estimated (indistinguishable from zero) for all norms measures. This may be due to simultaneity, as theoretical frameworks predict opposing effects of norms (higher wages would presumably cause workers to view work more favorably, but stronger NTW could indirectly depress wages by increasing labor supply).

Table 3: Effect of state-level norms on Labor Force Participation

VARIABLES	Effect of state-level norms on LFP			
	(1) anti_work	(2) ntw	(3) pro_labor	(4) unemp_stigma
anti-work (relevant vol-adj.)	-0.00574*** (0.00186)			
norm to work (relevant vol-adj.)		0.00277** (0.00108)		
pro-workers rights (relevant vol-adj.)			0.00397* (0.00225)	
unemp. stigma (relevant vol-adj.)				-0.000529 (0.00133)
<b>Controls</b>				
tweet count (state)	-2.07e-07 (4.43e-07)	-4.91e-07 (4.43e-07)	-2.01e-07 (4.29e-07)	-4.03e-07 (4.16e-07)
lagged unemp rate (state)	0.0858 (0.101)	0.0698 (0.102)	0.104 (0.101)	0.0899 (0.100)
state population	-7.31e-09*** (1.66e-09)	-6.94e-09*** (1.60e-09)	-6.69e-09*** (1.56e-09)	-6.57e-09*** (1.53e-09)
state UI replacement ratio	0.000949 (0.0315)	-0.00171 (0.0317)	-0.00728 (0.0313)	-0.00790 (0.0314)
Constant	0.319*** (0.0305)	0.319*** (0.0299)	0.312*** (0.0294)	0.313*** (0.0292)
<b>Mean LFP</b>	<b>0.782</b>	<b>0.782</b>	<b>0.782</b>	<b>0.782</b>
Observations	785,432	785,432	785,432	785,432
R-squared	0.113	0.113	0.113	0.113
Controls for demographics	✓	✓	✓	✓
Year and region FE	✓	✓	✓	✓

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Reflects individual LFP (binary) regressed on state-level norms and various controls

Standard errors clustered by region-year level in parentheses



Table 4: Effect of state-level norms on Employment

Effect of state-level norm to work on employment				
VARIABLES	(1) anti_work	(2) ntw	(3) pro_labor	(4) unemp_stigma
anti-work (relevant vol-adj.)	-0.00602*** (0.00174)			
norm to work (relevant vol-adj.)		0.00326*** (0.00108)		
pro-workers rights (relevant vol-adj.)			0.00311 (0.00238)	
unemp. stigma (relevant vol-adj.)				-0.00115 (0.00128)
<b>Controls</b>				
tweet count (state)	1.07e-07 (5.43e-07)	-2.05e-07 (5.15e-07)	6.58e-08 (5.59e-07)	-1.28e-07 (5.23e-07)
lagged unemp rate (state)	-0.490*** (0.101)	-0.510*** (0.102)	-0.474*** (0.103)	-0.489*** (0.102)
state population	-7.91e-09*** (1.72e-09)	-7.56e-09*** (1.66e-09)	-7.26e-09*** (1.68e-09)	-7.01e-09*** (1.66e-09)
state UI replacement ratio	-0.0123 (0.0321)	-0.0143 (0.0322)	-0.0212 (0.0329)	-0.0212 (0.0327)
Constant	0.254*** (0.0337)	0.255*** (0.0330)	0.247*** (0.0330)	0.247*** (0.0329)
<b>Mean Employment</b>	<b>0.742</b>	<b>0.742</b>	<b>0.742</b>	<b>0.742</b>
Observations	785,432	785,432	785,432	785,432
R-squared	0.108	0.108	0.108	0.108
Controls for demographics	✓	✓	✓	✓
Year and region FE	✓	✓	✓	✓

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Reflects individual employment (binary) regressed on state-level norms and various controls  
Standard errors clustered by region-year level in parantheses

Table 5: Effect of state-level norms on Wages

VARIABLES	Effect of state-level norms on wages			
	(1)	(2)	(3)	(4)
	anti_work	ntw	pro_labor	unemp_stigma
anti-work (relevant vol-adj.)	0.00137 (0.00256)			
norm to work (relevant vol-adj.)		-0.000602 (0.00186)		
pro-workers rights (relevant vol-adj.)			-0.00365 (0.00418)	
unemp. stigma (relevant vol-adj.)				0.00318 (0.00236)
<b>Controls</b>				
tweet count (state)	-2.03e-06* (1.16e-06)	-1.97e-06* (1.16e-06)	-2.13e-06* (1.18e-06)	-1.76e-06 (1.17e-06)
lagged unemp rate (state)	-0.185 (0.223)	-0.181 (0.224)	-0.199 (0.222)	-0.174 (0.224)
state population	4.02e-09 (4.34e-09)	3.93e-09 (4.34e-09)	3.81e-09 (4.28e-09)	2.99e-09 (4.41e-09)
state UI replacement ratio	0.149** (0.0610)	0.149** (0.0613)	0.151** (0.0614)	0.150** (0.0612)
state union coverage	-0.104 (0.132)	-0.104 (0.132)	-0.102 (0.132)	-0.0976 (0.132)
state min. wage	0.00697*** (0.00220)	0.00697*** (0.00220)	0.00685*** (0.00220)	0.00661*** (0.00218)
Constant	9.121*** (0.0756)	9.121*** (0.0758)	9.126*** (0.0749)	9.134*** (0.0755)
<b>Mean log wage</b>	<b>10.66</b>	<b>10.66</b>	<b>10.66</b>	<b>10.66</b>
Observations	503,621	503,621	503,621	503,621
R-squared	0.378	0.378	0.378	0.378
Controls for demographics	✓	✓	✓	✓
Year and region FE	✓	✓	✓	✓

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Reflects logged wage income (for full-time workers only) regressed on state-level norms and various controls  
Standard errors clustered by region-year level in parantheses

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