Measuring the influence of economic uncertainty on U.S. wages*

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Abstract

We study the impact of economic uncertainty on U.S. wages using online newspaper information. The data is collected via natural language processing (NLP) of leading news outlets between 2001 to 2018. We find that surges in general economic uncertainty are associated with reduced U.S. wages. Adding up the current and lagged effects leads to a 2.12 % decline in the average wage level. Our results are robust to alternative specifications of U.S. economic uncertainty with instruments based on foreign economic uncertainty.

*This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. We thank Peri Da Silva and Lei Lei Shen for their helpful comments. Huichen Yang provided excellent research support in the early stages of this project.

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1 Introduction

Economic uncertainty influences the risk associated with labor market events, such as employment changes (for example demotion from full-time to part-time positions or job losses), term-limited employment, or shifts in labor market laws (Mills and Blossfeld (2003), Blossfeld et al. (2006), Hofmeister and Blossfeld (2006)). Researchers have shown that accounting for uncertainty helps to determine fluctuations in trade volumes (Pierce and Schott, 2016, 2018); stock market dynamics (Liu and Zhang, 2015); and losses in firm-level capital investments (Gulen and Ion, 2016). This makes economic uncertainty understandably important and far-reaching for individuals and countries. In recent years, a large literature has investigated its impact within the fields of trade, economic policy, and macroeconomic performance. There as well, the prevailing assessment is that the influence of economic unpredictability has been exacerbated by fast-changing regulations, capital movements, financial crisis, and the growing globalization (Mills and Blossfeld (2003), Akinci et al. (2022)).[1]

In the US, wages represent the primary source of income. In 2019, 129 million tax filers reported wage income making up 68% of total income - greatly exceeding investment income (York, 2022). According to the Economic Policy Institute, among the bottom fifth households (in terms of earnings), nearly all income is exclusively wages. While most researchers agree that US wages have largely stagnated in recent decades (Wisman, 2013), there has been no shortage of domestic and global episodes of heightened economic uncertainty and complex monetary policy responses (Charles et al., 2018).[2] Baker et al. (2016) shows that policymaking uncertainty affects stock market price volatility, and lowers employment and investment within policy-sensitive sectors (infrastructure construction, healthcare, finance, and defense).

However, an important shortcoming of this literature has been the limited attention devoted to the link between uncertainty and wages.[3] The literature has shown that wage fluctuations can be explained by years of schooling and experience (Mincer, 1974), human capital factors (Goldin and Katz, 2008), and job tasks (Autor and Handel, 2013). Economic uncertainty also plays an important role in determining the future earnings and expected returns to education (Kodde (1986), Eaton and Rosen (1980), Williams (1979), Paroush (1976),

[1]The growing globalization has promoted mutual international interdependence but also created the possibility for far-reaching negative shocks. For this reason, the prevailing level of uncertainty has been magnified due to the global financial crisis of 2008, the European debt crisis of 2009, and other unpredictable events. (Ahir et al., 2022) argues that global economic uncertainty has significantly risen with the European debt crisis affecting countries outside of Europe.

[2]Examples include the Great Recession of 2007 and the controversial Emergency Economic Stabilization Act of 2008, the Gulf War (2003-2011), and the European Debt crisis (2009). Berger et al. (2017) finds that rising global uncertainty unambiguously depresses national growth rates, and raises inflation.

[3]Cacciatore and Ravenna (2021) does study the relationship between the two but rather focuses on business cycle-related uncertainty as opposed to the uncertainty of other kinds. The use of non-linear local projections and VAR (vector autoregressions) estimates supports their model prediction that measured uncertainty rises in contractionary phases even in the absence of uncertainty shocks.

Levhari and Weiss (1974), Kodde (1986)). Likewise, it influences immigrants' saving decisions which are largely based on wage differentials between host country and home country (Galor and Stark (1990); Dustmann (1997)). The same is true for women's employment, salaries, and fertility decisions (Kreyenfeld et al., 2012).

There is little doubt that the difficult measurement of uncertainty as an economic quantity has contributed to this gap. Unlike gross national products, prices, or total factor productivities, uncertainty is less easily quantifiable.[4] For this reason, researchers have instead relied on indexes to evaluate uncertainty on an agreed-upon scale (Baker et al., 2016). This measurement exercise had previously been complicated by scarce data availability, comparability, and systematic treatments. In recent years, however, newspapers have become increasingly digitalized, stored, and made publicly accessible often free of charge. Izade (2022) reports that several leading and local newspapers companies have stopped printing altogether as was predicted by the majority of journalism experts. Rising costs and the decline of print readership are two important factors driving the shift to online outlets. This change of direction has opened a rich well of data that can be gleaned via natural language processing (NLP) methods common in computer science but still underused in economics (Currie et al., 2020). Despite the increasing data availability from online newspapers (Einav and Levin, 2014) and the burgeoning econometric tools to analyze them (Athey and Imbens, 2019), the influence of economic uncertainty on wages has remained largely unexplored.

The contribution of this paper resides in estimating the influence of economic uncertainty on wages. We measure uncertainty by constructing a general U.S. index based on U.S. news information. We gather data at the industry level (aggregate level of 4-digit industries of IPUMS). Natural Language Processing (NLP) of 3,842 articles gathered between January 2001 and December 2018 from various journals is performed to build our uncertainty index. We also obtain comparable data from news outlets in Canada, Mexico, and China to supplement our analysis. Results show that an increase in U.S. economic uncertainty has significant adverse effects on U.S. wages. A one-standard-deviation increase in economic uncertainty leads to a 2.3 percent decline in wages. In addition, we show a supporting set of robustness tests that corroborate the initial findings.

The rest of the paper proceeds as follows. Section 2 discusses briefly the relevant literature. Section 3 describes the data, the construction of the economic uncertainty index, and the description of its main economic characteristics across industries and years. Section 4 describes our econometric approach, most closely related to Autor and Handel (2013) with an extension of the seminal Mincer (1974) wage regression. Section 5 describes the main results, while Section 6 discusses several robustness tests. Section 7 concludes the paper.

[4] A comparable enduring problem in economics is the classic utility measurement issue (Becker et al., 1964).

2 Literature review

2.1 Economic uncertainty and labor market decisions

According to Merton (1975), uncertainty generally affects five dimensions: (1) uncertainty about future capital income from marketable assets returns; (2) uncertainty about future labor income; (3) uncertainty about life expectancy; (4) uncertainty about the future investments opportunities; and (5) uncertainty about future consumption. At least four of these aspects are directly related to traditional economic analysis reflecting that uncertainty is crucial to the discipline. Economic uncertainty has drawn much attention from policymakers and researchers for decades, among other reasons because it can limit economic performance (Aastveit et al., 2013).

Kodde (1986) is a seminal study in this field arguing that economic uncertainty is closely linked to future earnings and therefore causes investment in human capital to be risky. This uncertainty may come from the unpredictable forces of demand and supply in the labor market, individuals' imperfect assessment of their own abilities, their future earnings, uncertainties in the job search process or, of course, the chancy match between earnings and education (Kodde, 1986). Economic uncertainty also affects human capital investment in terms of earnings taxation. Assuming a fixed labor supply, a proportional earnings tax wouldn't affect human capital investment because the tax reduces both the cost of investment and the returns to the same rate. However, with economic uncertainty, human capital investment can be affected by earnings' taxes through the change in the riskiness of human capital and the generation of income effects which could influence the individual's willingness to take risks (Eaton and Rosen, 1980). In other words, economic uncertainty lowers the incentive for human capital investment.

Uncertainty may also influence temporary migrants' with regard to remittances and savings, which plausibly differ from the case of permanent migrants or natives. Particularly, Galor and Stark (1990) show that immigrants save more than natives and that the uncertainty of future incomes increases the saving gap considering that lower future income will increase their marginal utility of wealth. Temporary migrants' decisions to go back also largely depend on future income streams which depend on economic uncertainty (Dustmann, 1997). More precisely, economic uncertainty in the home country's labor market will encourage migrants to stay in the host country if wages in the host country are larger, while a higher level of economic uncertainty in the host country will push migrants back to their home country. From this perspective, U.S. economic uncertainty increases instability in the U.S. labor market.

Economic uncertainty may also postpone women's family plans due to income unpredictability (Erosa et al., 2002). Childbearing is a crucial event requiring a long-term resource investment (Noguera et al., 2002). According to Kreyenfeld et al. (2012), uncertain economic conditions are negatively associated with fertility rates. Noguera et al. (2002) find that the labor force participation of women in countries with higher levels of economic uncertainty is extremely low and from this perspective, economic uncertainty imposes significant constraints on parenthood and career plans further promoting labor market instabilty.[5]

2.2 Online data mining

Online data on various topics is readily accessible online. The internet provides real-time information adequate for continuous collection, which can outperform questionnaires or survey data (Zhang and Verma, 2017). A growing number of researchers use online information for various investigations. Jang et al. (2018), for example, identify a number of hotel attributes extracted from online reviews of TripAdvisor® to better understand consumer needs. Liu (2006) uses data collected from the Yahoo® Movie Web site to examine the dynamic patterns of word-of-mouth (WOM) information. Dellarocas (2003) collects online information to study some important dimensions in the differences between Internet-based feedback mechanisms and traditional surveys. Tirunillai and Tellis (2012) aggregate user-generated content (UGC) from multiple websites to identify its potential relationship with stock market performance.

The newspaper is considered as one of the oldest form of media used to deliver information (McQuail (1994), Boczkowski (2005)). Nowadays, online newspapers have disrupted the norm by attracting many more readers, transforming the newspaper industry dramatically (Seelye, 2005). Many online newspapers are accessible worldwide, such as China Daily® from China, Financial Post® from Canada, Mexico News Daily® from Mexico, and U.S. News®. These newspapers can be collected free of charge and cover several years.[6] In the paper, we build U.S. news-based economic uncertainty index relying on U.S. news articles for the main estimation. Then using news articles collected from Canada, Mexico, and China we calculate a U.S. economic uncertainty index as well as economic uncertainty indexes for each country respectively. These additional procedures will be part of the robustness tests.

[5]Individuals are more likely to postpone having children in times of economic uncertainty (Hofmann and Hohmeyer, 2013). This is more likely to happen to female workers who have relatively higher incomes (Caucutt et al., 2002). When more women join the labor market, their wages and family plans are jointly affected by economic conditions and uncertainties. Germany, for example, has implemented family policy regulations to encourage females to join in the labor market before giving birth to children to mitigate the negative effects of economic uncertainties on them.

[6]The influential study of Baker et al. (2013) collected news-based data from the 1960s to 1990s to construct an economic policy uncertainty (EPU) index. Researchers have also constructed uncertainty indexes for other countries, such as Australia, Brazil, China, Canada, France, Germany, etc., with a similar approach (Baker et al. (2013), Cerda et al. (2016), Davis et al. (2019)). It's worth noting that newspapers may not only affect firms' and workers' immediate behaviors but also take some time to be fully effective. Therefore, it is necessary to examine the time-lagged influence of the EU effect generated based on newspapers (Lee et al., 2014).

3 Data

In this section, we describe the dataset used in this paper. First, we explain in more detail the construction of the U.S. economic uncertainty index and discuss variations within the time window, the industries with notably high/low uncertainty levels, and their associated wage fluctuations. Second, we discuss the other information gathered to investigate the effects of U.S. economic uncertainty on U.S. labor. In this case, we discuss the relationship between U.S. economic uncertainty and individual yearly wage across industries and years.

3.1 Economic uncertainty index

Baker et al. (2016) show that the U.S. economic policy uncertainty index is strongly correlated with stock price volatility for U.S. firms intensely exposed to federal purchases and that this adverse effect is driven by sector-specific economic uncertainty related to firms in the defense, health, and finance industries, subject to comprehensive regulatory norms, and some are dependent on government purchases.[7] This result suggests that industry-specific economic uncertainty is essential to better understand the general effects of uncertainty across sectors. Thus, considering the effects of industry-specific uncertainty is essential to understanding the impact on U.S. labor.

Our general U.S. economic uncertainty index is constructed following the strategy adopted by Baker et al. (2016). We generated the index based on economics-related news articles' frequency in four well-regarded newspapers circulating in the U.S. More specifically, we included information from news articles from the U.S. News® (founded in 1933), The Guardian® - U.S. edition (founded in 1821), Politico® (founded in 2007), and Livingston® (founded in 1945). Several reasons motivated us to choose these four outlets. First, they have been accessible electronically over the time window of interest (2001-2018). Second, they allow for the automatic selection of economics-related news articles, decreasing computational costs since the focus is to consider economic uncertainty's effects on U.S. labor markets at the industry and year levels.[8] Third, these news outlets do not impose technical restrictions on parsing words, representing an essential feature to employ the text-mining approach. Last, these four outlets do not present time window restrictions in the automated search for economic-related news, while some popular newspapers allow for the automated search only for

[7] They show that changes in economic policy uncertainty are negatively correlated to firm-level investment rates. This result applies to the average firm (i.e., beyond the firms in the defense, health, and finance industries).

[8] Baker et al. (2016) emphasizes aggregate levels of economic policy uncertainty. Their index was constructed using information from USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and Wall Street Journal. Many of these outlets have the aforementioned technical restrictions that would make the construction of an economic uncertainty index with industry variation very time-consuming. Not to mention that all these outlets require a subscription.

articles published in the most recent years or even months.[9]

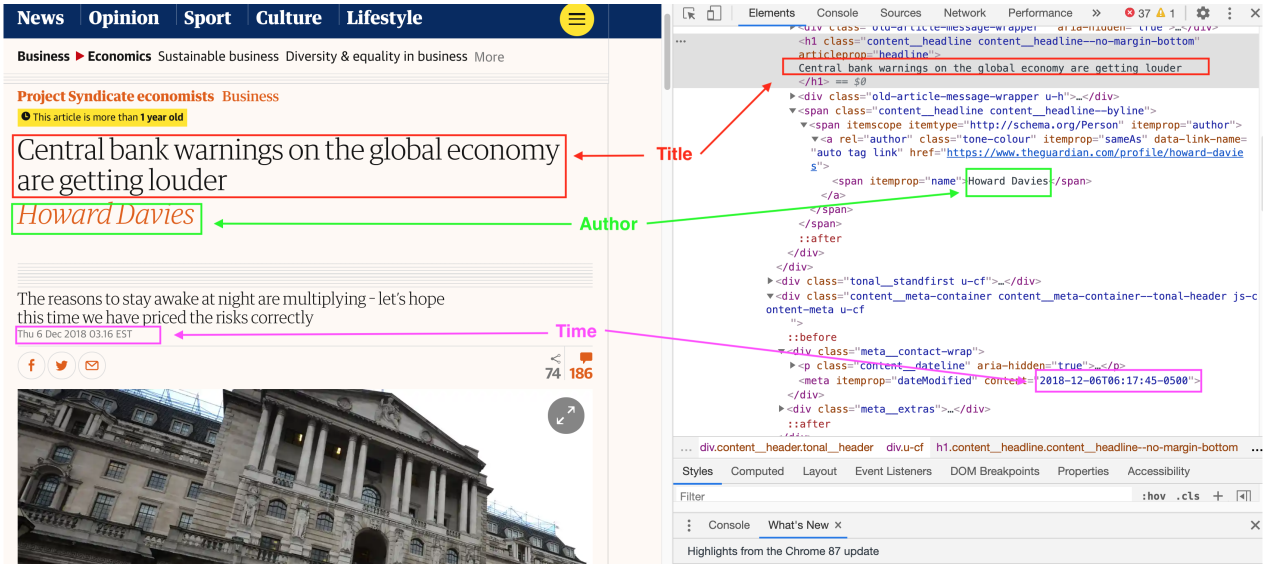

Figure 1: Labels on the HTML source page. Red rectangles indicate the title parsed by the code while the green rectangles contain the authors' names and the pink rectangles show the release date of the article. Article sources: Davies (2018).

We developed a procedure using Python with the Selenium framework to parse and download the news data using the corresponding labels on the HTML source page, such as $< div >$, $< p >$, and $< li >$. As indicated above, an essential point for us involves identifying the industry associated with the relevant news that occurred in the U.S. In this study, we defined an industry using the aggregate industries of IPUMS. An example may help clarify how the parsing of words helps us determine the industry in question. In the case of the industry of "Finance and Insurance",[10] we labeled news related to this industry if it contains at least one of the combinations of words "finance" and "insurance" or any representative words/phrases under its sub-categories.

Figure 1 shows an example where the red rectangles indicate the title words parsed by the code. Next, the green rectangles indicate the author and the pink rectangles indicate the time, where we only keep information from 2001 to 2018. The elements we parsed and extracted included the news title, time, tags, content, and author. We downloaded 3,842 news articles from January 2001 to September 2019, but eventually only used the news articles from January 2001 to December 2018 to match the other dataset available, such as wages, employment information, industries, and demographic components. Table 1 includes examples of economic-

[9] The Wall Street Journal allows the automated search for articles published in the last twelve months and the USA Today for articles published in the previous five months.

[10] The entire industry of "Finance and Insurance" includes Banking and related activities (code: 6870), Savings institutions, including credit unions (code: 6880), non-depository credit and related unions (code: 6890), Securities, commodities, funds, trusts, and other financial investment (code: 6970), and Insurance carriers and related activities (code: 6990).

related articles downloaded from the selected four news sources in different years. The words in bold assist us in identifying industries mentioned in these news articles, such as real estate, education, health care, and agriculture.

Table 1: Example of news text analysis

News source	Year	News body
The Guardian	2018	Since 1900, wine investments have outperformed cash, government bonds and **real estate**.
US News	2017	...according to the Department of Commerce, **education services** ranked seventh among all U.S. service exports in 2015, as international students enrolled in U.S. educational institutions brought in more than \$35.7 billion for the economy via tuition and living expenses
POLITICO	2015	...but they ran into stiff opposition from Australia and five other countries who worried that would bust their **health care** budgets and keep the medicines out of reach for poorer patients by delaying the introduction of cheaper generic versions
Livingston	2015	For example, in 2012, WTO told the U.S. Department of **Agriculture** that labeling cuts of red meat with "Product of U.S." was no longer sufficient.

We followed the method of Baker et al. (2016) to build this index at two levels, including $EU_{s,t}$ and EU_t. $EU_{s,t}$ is the economic uncertainty in industry s at time t. We first present the steps to create $EU_{s,t}$.

Step 1: At first, we generated the frequency of economic-related news that contained uncertainty-related words. These words are based on the uncertainty terms constructed by Caldara et al. (2020), and some additional relevant words, such as "uncertainty", "uncertain", "not certain", "unsure", "not sure", "unpredictable", "unknown". It varies across newspapers, industries, and years.

$$U_{i,s,t} = \sum_{q} U_{q,i,t} F_{q,i,s,t}, \tag{1}$$

where $U_{q,i,t}$ is the number of news articles relevant to the U.S. economy with uncertainty-related words in each article q in newspaper i and year t; $F_{q,i,s,t}$ is 1 if industry s is mentioned in each article q in newspaper i and year t and is 0 otherwise.

Step 2: Then, following Baker et al. (2016) strategy, we scale the $U_{i,s,t}$ by the total number of articles in the same newspaper and year, then standardize it to the unit standard deviation from 2001 to 2018, and lastly average across all the brands of newspapers selected by industry and year.

$$z_{s,t} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\frac{U_{i,s,t}}{T_{i,t}}}{std\left(\frac{U_{i,s,t}}{T_{i,t}}\right)}\right], \tag{2}$$

where $T_{i,t}$ is the total number of articles in newspaper i and year t; N is the number of newspapers we selected.

Step 3: Finally, we normalize the $z_{s,t}$ to a mean of 100 from 2001 to 2018.

$$EU_{s,t} = \frac{100z_{s,t}}{\frac{1}{K}\sum_{k=1}^{K} z_{s,t}}, \tag{3}$$

where EU represents the economic uncertainty and K is the total number of observations in this analysis.

Generating an economic uncertainty index at the annual level should follow similar steps. The following 3 equations show the steps to construct the index at the annual level

$$U_{i,t} = \sum_{q} U_{q,i,t} \tag{4}$$

$$z_{t} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\frac{U_{i,t}}{T_{i,t}}}{std\left(\frac{U_{i,t}}{T_{i,t}}\right)}\right] \tag{5}$$

$$EU_{t} = \frac{100z_{t}}{\frac{1}{K}\sum_{k=1}^{K} z_{t}} \tag{6}$$

Figure 2 shows the top U.S. 5 industries with the highest economic uncertainty index on average over the past 10 years. These industries include “Arts, Entertainment, and Recreation”, “Agriculture, Forestry, Fishing, and Hunting”, “Manufacturing”, “Finance and Insurance”, and “Construction”. Figure 3 shows the yearly evolution of the economic uncertainty index at the annual level from 2001 to 2018. The overall tendency of this index implies an increase in economic uncertainties over time. Particularly, the index peaks in 2001 because of the September 11 terrorist attacks, and drastically falls during the following year. Likewise, it spikes again with the U.S. and its allies’ invasion of Iraq in 2003-2004 and significantly falls in 2005. The index seems to increase considerably in early 2006 after Hurricane Katrina passed southeast of New Orleans and falls in 2007. However, the financial crisis has pushed the index up since 2008. In this case, the increase in economic uncertainty is likely related to several economic events and governments’ concern with the increase in good prices and unemployment rates, and the temptation to use monetary policy and fiscal policy as remedies. The economic uncertainty index remained stable at high levels from 2008 to 2013 and reached another peak during the fiscal cliff and government shutdown in 2014. The economic tension was relieved after 2015 but deteriorated to its worst level ever in 2018 when the biggest trade war occurred between the U.S. and China.

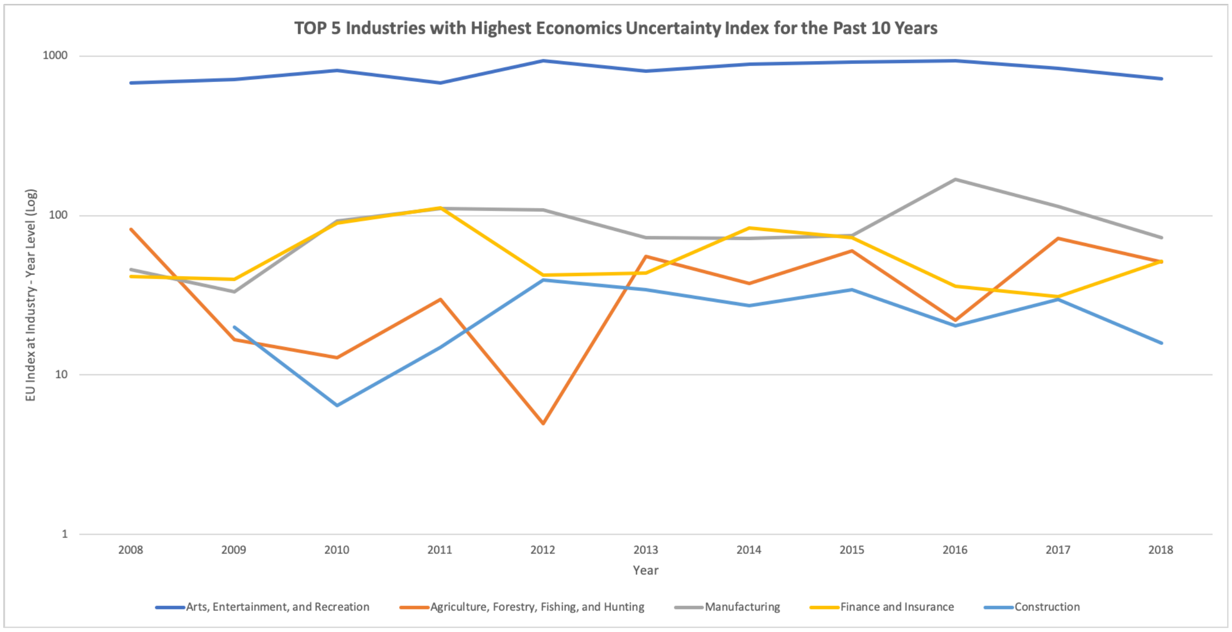

Figure 2: Top 5 industries with highest economic uncertainty for the past 10 years. Arts, Entertainment, and recreation industries record the highest level of economic uncertainty. Periods of high/low uncertainty appear to consistently affect the four other industries.

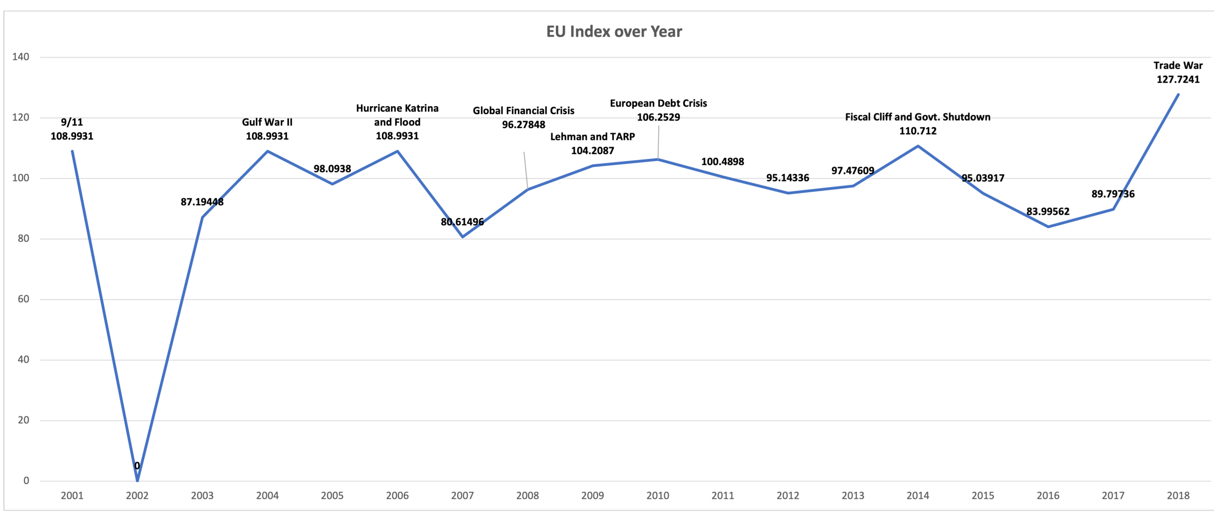

Figure 3: Economic uncertainty index between 2001 and 2018. Major events like the attacks of 9/11, Hurricane Katrina, and the Financial Crisis of 2007 are clearly marked by surges in economic uncertainty. This adds credibility to our index given that major global events coincide with uncertainty shocks.

3.2 Wage data and other labor information

The U.S. labor-related information is collected from IPUMS USA (Integrated Public Use Microdata Series), including wages, employment information, industries, and several demographic components, such as gender, race, ethnicity, etc. 19 industries at the aggregate level are selected from the aggregate level of 4-digit industries of IPUMS (Ruggles et al., 2015). Figure 4 reports the yearly growth of wages for the industry with the highest economic uncertainty index compared to the one with the lowest index, and the mean wage of all selected individuals over time. The yearly growth of wage is computed based on the percentage change between two successive years and the data starts from 2001, so the figure covers from 2002 to 2018. We find that the change in wages is in line with the change in the economic uncertainty index. Specifically, wages appear more volatile in industries with a high economic uncertainty index (Arts, Entertainment, and Recreation) compared to industries with a low index such as Public Administration.

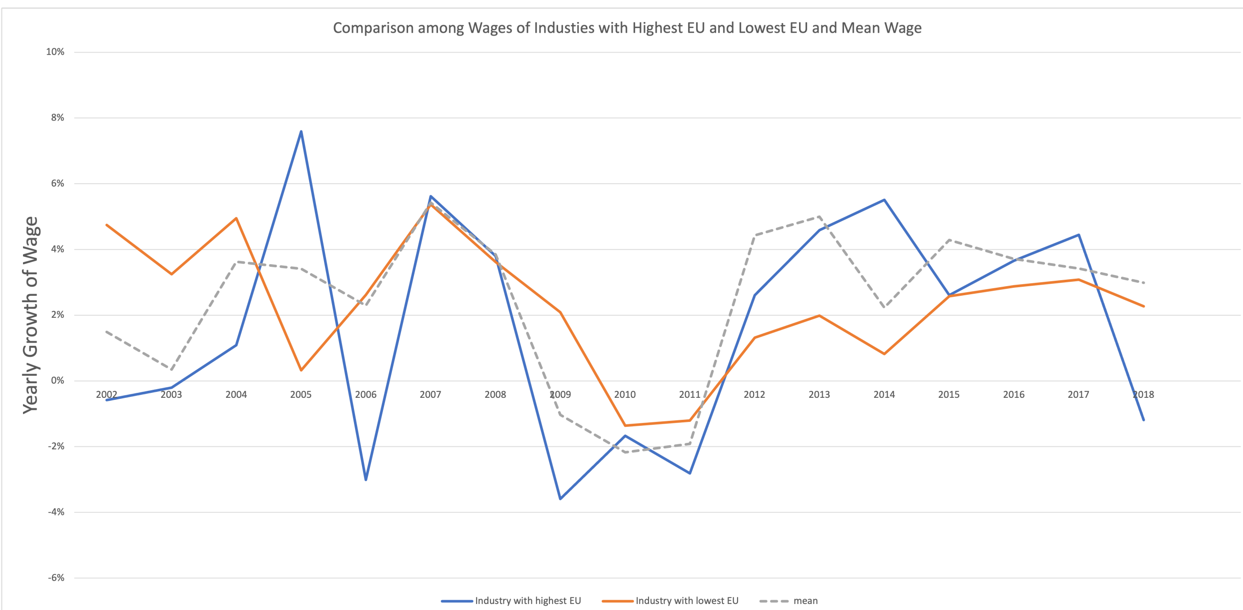

Figure 4: Wage changes among industries with highest/ lowest EU and mean. Computations are based on the percentage change between two consecutive years. Wage changes are in line with important episodes of fluctuating economic uncertainty.

Table 2 shows summary statistics for the U.S. economic uncertainty index with industry-year levels of aggregations. We have a total of 342 measures of the main variable $EU_{s,t}$. Moreover, we control for the lagged values of economic uncertainty, given that the effects of this index may take some time to affect the contracts related to wages. It is clear from the information available in Table 2 that the data on the index is a bit noisy as the standard deviation corresponds to around three times the standardized average values. Besides the economic uncertainty index and its lag which vary by year and industry only, all other variables vary by individual labor. In total, there are 26,011,025 observations, including 13,306,000 males and 12,705,025 females whose average age is 41.67 and average education year is 13.28. The average yearly wage for all individuals in the data set is 34,882.48 U.S. dollars.

Table 2: Summary statistics

	N	Mean	SD	Min	Max
Economic uncertainty indexes					
$EU_{s,t}$	342.000	100.000	314.713	0.000	1828.385
$EU_{s,t-1}$	323.000	99.601	315.036	0.000	1828.385
U.S. labor market after being weighted					
Age	26,011,025	41.665	14.878	16.000	97.000
Education year	26,011,025	13.281	2.535	0.000	17.000
Potential experience	26,011,025	22.390	14.868	0	89.000
Yearly wage (U.S. dollars)	26,011,025	34,882.480	48,399.130	0.000	736,000

4 Empirical methodology

The original Mincer (1974) wage regression estimated the market return to human capital investment, which contributed greatly to subsequent empirical research. Autor and Handel (2013) then provided a hedonic model of wages based on the Mincer (1974) wage regression as follows:

$$lnW_i = \alpha + \beta_1 S_i + \beta_2 Exp_i + \beta_3 Exp_i^2 + \beta_4 X_i + \epsilon_i, \tag{7}$$

where lnW_i is the log wage for individual i, S_i is years of completed schooling for individual i, Exp_i is the potential experience for individual i, X_i is a vector of demographic components for individual i, such as gender, race, ethnicity, etc. In addition, β_1 is the wage return to education and β_2 is the wage return to experience. Both β_1 and β_2 are expected to be positive. Considering the effect of economic uncertainty is enormous, it would be interesting to see how economic uncertainty would affect wages over time. We, therefore, augmented this model by adding two more terms:

$$lnW_{i,s,t} = \alpha_t + \theta_s + \lambda_1 EU_{s,t} + \lambda_2 EU_{s,t-1} + \beta_1 S_{i,s,t} + \beta_2 Exp_{i,s,t} + \beta_3 Exp_{i,s,t}^2 + \beta_4 X_{i,s,t} + \epsilon_{i,s,t}, \tag{8}$$

where $EU_{s,t}$ and $EU_{s,t-1}$ are the concurrent and lagged values of economic uncertainty, respectively, and they vary by industry and year, while all other variables vary by individual, industry, and year. α_t are year fixed effects and θ_s are industry fixed effects. We kept the standard errors to be robust to heteroskedasticity in all of the models and clustered the standard errors of the index at the year-industry level considering that it may be constant within some industries across years while varying for other industries over time.

5 Results

We now turn to the estimation results and first discuss the estimation of the baseline expression, which investigates the effects of U.S. economic uncertainty on wages. Table 3 reports the results. Column (1) corresponds to Equation (7) which is the hedonic model of wages from Autor and Handel (2013) serving as a benchmark to develop subsequent specifications. Columns (2) and (3) include only the economic uncertainty variables. Columns (4) and (5) include both the economic uncertainty variables and all other variables used in the hedonic model of wages. Our baseline specification corresponds to column (5), which matches the explanatory variables described in Equation (8). Notice that our concurrent and lagged measures of economic uncertainty are scaled by 0.0001. As indicated at the bottom of table 3, all specifications control for industry and year fixed effects. Column (1) reports the estimated effect of education, potential experience, and other demographic factors, which are consistent with Autor and Handel (2013) results.

Column (2) reports the estimated effect of $EU_{s,t}$ on wage. The coefficient on $EU_{s,t}$ is -0.513, and it is statistically significant at the 1% level. This result suggests that a one-standard-deviation increase in this variable is associated with an average decrease of 1.6 (0.513 $\times$ 314.713 (S.D. of $EU^{j}_{s,t}$) $\times$ 0.0001 $\times$ 100 $\%$) percent in wage.

The specification used in column (3) adds the one-year lagged value of uncertainty ($EU_{s,t-1}$) to the regression. The results in column (3) indicate that the coefficients of the concurrent and lagged values of the economic uncertainty index are negative and statistically significant at the 1% level. The results in columns (4) and (5) show that including additional variables as in Autor and Handel (2013) do not alter the total effect of EU on wage. The result in column (5), corresponding to Equation (8), suggests that a one-standard-deviation increase in current and lagged economic uncertainty index leads to a 1.12 (0.357 $\times$ 314.713 (S.D. of $EU_{s,t}$) $\times$ 0.0001 $\times$ 100 $\%$) percent and 1 (0.315 $\times$ 315.036 (S.D. of $EU_{s,t-1}$) $\times$ 0.0001 $\times$ 100 $\%$) percent decrease in wage, respectively. Adding up the effects of concurrent and lagged values of the index then suggests a total 2.12 percent decline in wages. Moreover, the results confirm the expectations discussed in the introductory section and the coefficients of all other variables are nearly equal to those in column (1).

Table 3: OLS regressions of log wages on economic uncertainty

	Dependent variable: Yearly wage (log)				
	(1)	(2)	(3)	(4)	(5)
Uncertainty$_{s,t}$		-0.513***	-0.391***	-0.509***	-0.357***
		(0.129)	(0.164)	(0.081)	(0.092)
Uncertainty$_{s,t-1}$			-0.326***		-0.315***
			(0.135)		(0.089)
Less than high school	-0.212***			-0212***	-0.208***
	(0.006)			(0.006)	(0.006)
College	0.413***			0.413***	0.412***
	(0.006)			(0.006)	(0.006)
Post college	0.978***			0.978***	0.980***
	(0.014)			(0.014)	(0.014)
Experience	0.085***			0.085***	0.085***
	(0.001)			(0.001)	(0.001)
Experience^2	-0.001***			-0.001***	-0.001***
	(0.000)			(0.000)	(0.000)
Male	0.349***			0.349***	0.349***
	(0.005)			(0.005)	(0.005)
White	0.023***			0.023**	0.022***
	(0.004)			(0.004)	(0.005)
Black	-0.136***			-0.136***	-0.139***
	(0.007)			(0.007)	(0.007)
Hispanic	-0.079***			-0.079***	-0.079***
	(0.008)			(0.008)	(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	19,199,574	19,199,574	18,700,181	19,199,574	18,700,181
R-squared	0.359	0.144	0.144	0.359	0.359

Notes: The dependent variable is the annual wage expressed on the logarithmic scale. Economic uncertainty is obtained from the natural language processing of news information and scaled by 0.0001 for ease of interpretation. It is recorded annually at the industry level. The reference group is non-Hispanic high school females with races other than white and black. Standard errors are robust to heteroskedasticity and displayed in between parenthesis. Clustering is performed at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**) and 1% (***) levels.

6 Sensitivity analyses

Several additional questions are raised by the baseline results which we aim to address in this section. First, in order to ensure that specific industries and years do not drive the variation in the economic uncertainty index, we conducted a robustness test by first finding out the top 5 industries that have the highest standard errors from the regression of this index on all industries and years. These five "outliers" are " Arts, entertainment, and recreation", " Manufacturing", "Finance and insurance", " Wholesale trade", and "Utilities" which are sorted by the standard errors in this regression from the highest to the lowest. We then removed them each at a time from the baseline regression in column (5) of table 3.

Table 4: Robustness test after removing outliers.

	Dependent variable: Yearly wage (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty$_{s,t}$	-0.240	-0.358***	0.368***	-0.348***	-0.343***	-0.274
	(0.256)	(0.093)	(0.084)	(0.096)	(0.095)	(0.495)
Uncertainty$_{s,t-1}$	-0.307	-0.375***	-0.321***	-0.310***	-0.306***	-1.146**
	(0.268)	(0.098)	(0.087)	(0.091)	(0.090)	(0.544)
College	0.410***	0.404***	0.412***	0.411***	0.413***	0.396***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)
Experience	0.084***	0.087***	0.086***	0.085***	0.085***	0.086***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Outliers removed	Arts, entertainment, and recreation	Manufacturing	Finance and insurance	Wholesale trade	Utilities	All five excluded
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,308,143	16,492,899	17,726,244	18,134,926	18,505,485	13,911,274
R-squared	0.357	0.357	0.354	0.360	0.357	0.348

Notes: Outliers industries are those with the greatest uncertainty variances. The dependent variable is the annual wage expressed on the logarithmic scale. Economic uncertainty is obtained from the natural language processing of news information and scaled by 0.0001 for ease of interpretation. Outlier industries are those with the largest distance from the average uncertainty in the sample. It is recorded annually at the industry level. The reference group is non-Hispanic high school females with races other than white and black. Additional variables include all demographic and education variables displayed in Table 3. Standard errors are robust to heteroskedasticity and displayed in between parenthesis. Clustering is performed at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**) and 1% (***) levels.

The results are reported in Table 4 and show that the industry "Arts, entertainment, and recreation" does affect the results shown in column (1) such that the economic uncertainty effects are still negative but not significant when removing that industry, while other industries wouldn't change the effects of economic uncertainty according to column (2) to (5). Moreover, lagged uncertainty is still significant at the 5% level and negative in the baseline regression in column (6) when we removed all five outlier industries. Meanwhile, the coefficient R-squared remains similar to its value in Table 3 column (5).

Table 5: Robustness test separating the contemporaneous and lagged effect of uncertainty

	Dependent variable: Yearly wage (log)				
	(1)	(2)	(3)	(4)	(5)
Uncertainty$_{s,t}$	-0.513***		-0.509***		-0.357***
	(0.129)		(0.081)		(0.092)
Uncertainty$_{s,t-1}$		-0.455***		-0.433***	-0.315***
		(0.123)		(0.097)	(0.089)
College			0.413***	0.412***	0.412***
			(0.006)	(0.006)	(0.006)
Experience			0.085***	0.085***	0.085***
			(0.001)	(0.001)	(0.001)
Experiences^2			-0.001***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Additional variables	No	No	Yes	Yes	Yes
AIC	5.56×10^7	5.42×10^7	5.01×10^7	4.88×10^7	4.88×10^7
BIC	5.56×10^7	5.42×10^7	5.01×10^7	4.88×10^7	4.88×10^7
Observations	19,199,574	18,700,181	19,199,574	18,700,181	18,700,181
R-squared	0.144	0.144	0.359	0.359	0.359

Notes: The dependent variable is the annual wage expressed on the logarithmic scale. Economic uncertainty is obtained from the natural language processing of news information and scaled by 0.0001 for ease of interpretation. It is recorded annually at the industry level. The reference group is non-Hispanic high school females with races other than white and black. Additional variables include all demographic and education variables displayed in Table 3. Standard errors are robust to heteroskedasticity and displayed in between parenthesis. Clustering is performed at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**) and 1% (***) levels.

In order to avoid the potential collinearity between the measure of uncertainty and its lagged value, we replicated the results in table 3 but separated them into two regressions. The results are reported in Table 5. Columns (1) and (2) only show the association between the concurrent economic uncertainty index and wages and the lagged index and wages, respectively. Columns (3) and (4) correspond to the baseline regression (7) adding the concurrent or lagged values of the index. Column (5) replicates the result in column (5) of Table

3. Reported in this table, both contemporaneous and lagged uncertainty have a significantly negative effect on wages in the U.S. labor market. In addition, we note that the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) criteria for model selection suggest that the specifications used in columns (4) and (5) are selected compared to the specifications used in other columns. Given the magnitude of the economic uncertainty effects, we keep both measures of uncertainty in the subsequent regressions. This is consistent with the assumption that the economic uncertainty index generated based on newspapers may take a year of time to fully affect contracts related to wages.

Another potential concern with our results is that we have so far relied on U.S.-based media outlets to measure the economic uncertainty index and have proved that the index based on U.S. news has a negative impact on U.S. labor market wages. Assuming that U.S. economic uncertainties can also be discussed in foreign newspapers, we also constructed a U.S. economic uncertainty index based on newspapers issued by the three leading U.S. trade partners (US Census). Among the select three countries, Canada and Mexico are physically close. For Canada, we relied on information from the Financial Post® and the Maclean's®. Notice that both outlets have been reliable information sources since the beginning of the 20th century. In Mexico's case, we used information from the Yucatan Times® which began operations on December 4 of 2010, the Banderas News® which is one of Puerto Vallarta's most active platforms, and the Mexico News Daily® which was launched in June 2014 as a digital publication. In China's case, we used information from China Daily® which is an English-language daily newspaper established in 1981, the official English-language website of China's news service ECNS.cn®, and the newspaper the Shine®. Notice that the last source was established in 1999 and has become the largest English-language newspaper in East China.

The results are displayed in Table 6. Following the same strategy used in Table 3 but excluding column (1) which is the benchmark reflecting Autor and Handel (2013) model. Columns (1) to (12) report the effects of concurrent economic uncertainty as well as the effects of both the concurrent and the lagged economic uncertainty on wages with and without controlling for other variables in the three countries. The economic uncertainty index constructed using Canada's newspapers does not have a significant effect on U.S. wages. The indices constructed by Mexico's and China's newspapers are negative in all columns and largely significant. The coefficients on the additional variables in all three panels are in line with the literature and our previous results but are not reported for ease of presentation.

Additionally, we also want to rule out the possibility of an endogenous link between wages and economic uncertainty based on U.S. news or an omitted "confounder" that influences both wages and economic uncer-

Table 6: Robustness test using news from US trade partners

	Dependent variable: Yearly wage (log)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Using news from Canada				Panel B: Using news from Mexico				Panel C: Using news from China			
Uncertainty$_{s,t}$	0.002	0.076	-0.017	0.047	-0.088	-0.012	-0.078**	-0.024	-0.712***	-0.623	-0.599***	-0.254
	(0.166)	(0.165)	(0.125)	(0.114)	(0.056)	(0.047)	(0.040)	(0.035)	(0.249)	(0.655)	(0.168)	(0.386)
Uncertainty$_{s,t-1}$		-0.006		-0.025		-0.105***		-0.067**		-0.733***		-0.551***
		(0.137)		(0.096)		(0.038)		(0.028)		(0.244)		(0.147)
College			0.413***	0.412***			0.413***	0.412***			0.413***	0.412***
			(0.006)	(0.006)			(0.006)	(0.006)			(0.006)	(0.006)
Exper.			0.085***	0.085***			0.085***	0.085***			0.085***	0.085***
			(0.001)	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)
Exper.^{2}			-0.001***	-0.001***			-0.001***	-0.001***			-0.001***	-0.001***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. Vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. (1,000)	19,199	18,700	19,199	18,700	19,199	18,700	19,199	18,700	19,199	18,700	19,199	18,700
R-squared	0.144	0.144	0.359	0.359	0.144	0.144	0.359	0.359	0.144	0.144	0.359	0.359

Notes: The dependent variable is the annual wage expressed on the logarithmic scale. Economic uncertainty is obtained from the natural language processing of news information and scaled by 0.0001 for ease of interpretation. It is recorded annually at the industry level. The reference group is non-Hispanic high school females with races other than white and black. Additional variables include all demographic and education variables displayed in Table 3. Standard errors are robust to heteroskedasticity and displayed in between parenthesis. Clustering is performed at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**) and 1% (***) levels.

tainty and, therefore, affects the conclusion of this paper. It is possible that fluctuations in the U.S. labor market may affect wages which may in turn influence the measure of economic uncertainty mentioned in the U.S. news. Or alternatively, unemployment rate increases or inflation rate decreases could affect both wages and economic uncertainty generated from U.S. news. In order to estimate the causal impact of U.S. economic uncertainty on wages in the U.S. labor market, we need an instrument that has an exogenous variation. We argue that the other countries' economic uncertainty index and their one-year lagged value generated based on their own newspapers about their own economy could be a good instrument, given that other countries' economic uncertainty indexes can be correlated with U.S. economic uncertainty index because of globalization (i.e., free flow of goods), but they should not have a direct effect on U.S. wages due to immigration restrictions (i.e., limited flow of people).

For constructing these instrument variables, we first collected economic-related news articles from the other three countries and then re-constructed the concurrent and one-year lagged values of the economic uncertainty index for each based on their own news articles regarding their own economy. Next, we averaged the concurrent and one-year lagged values of such indices among the three countries at the industry and year levels. Lastly, we followed the specifications in Table 3 columns (2) to (5) to regress the effect of U.S. economic uncertainty index on wages of U.S. labor market via the instruments of the concurrent and the lagged values of the other three countries' average economic uncertainty index, while clustering the standard errors of the economic uncertainty index at year - industry level and controlling for year fixed effects and industry fixed effects. In addition, the standard errors are robust to heteroskedasticity in all the specifications in this table.

Table 7 reports the two-stages least square regression results with these instruments. The results from the first stage regressions indicate a significant positive association between the concurrent and the lagged values of U.S. economic uncertainty and the instruments from the other countries. Results from the second stage regression show that both the coefficients of the concurrent and the lagged index are negative. Particularly, the contemporaneous level of economic uncertainty is highly significant in all specifications. It is worth noting that the total effects of both concurrent economic uncertainty and its lag on wages via instruments in column (4) of Table 7 is close to the total effects of both concurrent index and its lag in column (5) of table 3. The coefficients of all other variables are consistent with expectations. The instruments of other countries' economic uncertainty and its lag largely confirm the expectation of the negative economic uncertainty's impact on wages.

Finally, from figure 3, we found that the economic uncertainty index at the year level in 2002 is zero. This may be problematic because it implies that there were no uncertainty-related words found in the selected

Table 7: IV regressions (Two-stages least squares)

	Dependent variable: Yearly wage (log)			
	(1)	(2)	(3)	(4)
	Second stage			
Uncertainty$_{s,t}$	-0.613**	-0.578**	-0.484***	-0.438***
	(0.241)	(0.229)	(0.161)	(0.139)
Uncertainty$_{s,t-1}$		-0.074		-0.095
		(0.901)		(0.645)
College			0.412***	0.412***
			(0.006)	(0.006)
Experience			0.085***	0.085***
			(0.001)	(0.001)
Experience^2			-0.001***	-0.001***
			(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Additional variables	Yes	Yes	Yes	Yes
Observations	18,700,181	18,700,181	18,700,181	18,700,181
R-squared	0.144	0.144	0.359	0.359

Notes: The two-stage least-squares estimates are computed by instrumenting for US economic uncertainty using uncertainty indexes of other countries. First stage parameters are omitted and available upon request. The dependent variable is the annual wage expressed on the logarithmic scale. Economic uncertainty is obtained from the natural language processing of news information and scaled by 0.0001 for ease of interpretation. It is recorded annually at the industry level. The reference group is non-Hispanic high school females with races other than white and black. Additional variables include all demographic and education variables displayed in Table 3. Standard errors are robust to heteroskedasticity and displayed in between parenthesis. Clustering is performed at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**) and 1% (***) levels.

newspapers. It may be true that the U.S. economy went smoothly that year, or it may be caused by insufficient data collected that year. In order to avoid the index outliers generated in the year 2002, We conducted a robustness test by selecting all the data after 2002 and running the same specifications in Table 3. As reported in Table 8, results show that both the concurrent economic uncertainty index and its one-year lag are still negative and statistically significant after removing data in the years 2001 and 2002. Meanwhile, the effects of all other variables are consistent with the results in Table 3.

Table 8: Robustness test excluding data from 2002

	Dependent variable: Yearly wage (log)				
	(1)	(2)	(3)	(4)	(5)
Uncertainty$_{s,t}$		-0.419**	-0.231	-0.448***	-0.299***
		(0.171)	(0.190)	(0.111)	(0.110)
Uncertainty$_{s,t-1}$			-0.365***		-0.290***
			(0.141)		(0.087)
College	0.411***			0.411***	0.411***
	(0.006)			(0.006)	(0.006)
Experience	0.085***			0.085***	0.085***
	(0.001)			(0.001)	(0.001)
Experience^2	-0.001***			-0.001***	-0.001***
	(0.000)			(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Additional variables	Yes	No	No	Yes	Yes
Observations	18,254,752	18,254,752	18,254,752	18,254,752	18,254,752
R-squared	0.358	0.144	0.144	0.358	0.358

Notes: The dependent variable is the annual wage expressed on the logarithmic scale. Economic uncertainty is obtained from the natural language processing of news information and scaled by 0.0001 for ease of interpretation. It is recorded annually at the industry level. The reference group is non-Hispanic high school females with races other than white and black. Additional variables include all demographic and education variables displayed in Table 3. Standard errors are robust to heteroskedasticity and displayed in between parenthesis. Clustering is performed at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**) and 1% (***) levels.

7 Conclusion

This paper provides a novel way to study the effects of economic uncertainty on U.S. wages. The baseline results rely on constructing an economic uncertainty index based on news articles published by four major U.S. newspapers. This index controls for the presence of a wide set of economic events over the years, such as the financial crisis, the fiscal cliff, government shutdown, international trade wars, etc. The baseline specification shows that an increase in economic uncertainty tends to reduce wages in the U.S. labor market. Moreover, these results are economically meaningful. We find that a one-standard-deviation increase in U.S. economic uncertainty index leads to a combined decline of 2.12 percent in U.S. wages. In addition, the results are robust to the specifications when we remove the industry outliers from the baseline regression, when we remove year 2001 and year 2002 to avoid zero indexes, and when we use the average of other countries' own economic uncertainty indices as an instrument. The results are also supported by constructing U.S. economic uncertainty index using newspapers issued by other countries. Above all, it is reasonable to say that the baseline economic uncertainty index has a significant effect on wages and that controlling such uncertainty will maintain a stable labor market in the U.S.

This paper has profound implications for policymakers and political leaders in both local and international settings. It utilizes text mining skills to extract key information from numerous pieces of online news articles that efficiently and effectively predict wages in the U.S. labor market. It implies that economic uncertainty reduces wages and therefore hampers efforts to develop the economy. Reducing economic uncertainty (e.g. by avoiding trade wars and spelling out policies to address high unemployment) could be a crucial component to sustaining labor market health and therefore the whole economy.

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