The Quantile Impacts of Real Competition on Industrial Wage Inequality in the United States, 1998-2018

Doctoral Dissertation, Second Chapter, First Draft

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Competition between firms has a substantial impact on wage inequality between workers. The classical political economics literature proposes that turbulent dynamics of real competition within and between industries provide the framework for wage bargaining between workers and firms. Practial limits to wage growth are given turbulently equalizing (incremental profit rates and within-industry cost differentials) and persistently different factors (capital intensity and share of labor cost in total cost). The former provide the link between competition and wage growth, while the latter are responsible for persistent industrial wage premiums. We combine employee level data from the CPS and industry level data from BEA industry accounts from 1998-2018 and find that these impacts are substantial and of unambiguous signs but differential magnitude between income quantiles in those industries where both incremental profit rates and wage growth participate in turbulent equalization.

1 Introduction

Industrial wage inequality, the phenomenon that demographically similar persons with identical occupations earn different wages in different industries, appears as a social injustice as well as an economic puzzle. In general, increasing wage inequalities in the United States have been thoroughly documented since the 1970s (Acemoglu and Autor 2011), with early investigations into the industrial dimension going back as early as the mid of the century (Dunlop 1948; Slichter 1950). The literature has consistently observed an intimate relationship between unequal wages and structural differences on the employer side (Howell 1989; Du Caju, Rycx, and Tojerow 2011; Song et al. 2019). In this paper, I extend the analysis of industrial income inequality to the full wage curve to do justice to the inherently distributional character of income inequality.

When we investigate inequality-driving factors, there is little reason to expect that the average effect on inequality is the same for all segments of the wage distribution. Neither is it intuitive to expect that different factors have the same effects on the same segments. For example, the ability to attract workers by offering them higher wages might manifest more often among high-earning specialists, while restrictions to pay increases might be more important for less well paid groups of workers.

Recently, classical political economists started applying their insight into the dynamics of competition to structural determinants of wage bargaining and income inequality (Botwinick 2018; Shaikh, Papanikolaou, and Wiener 2014; Mokre and Rehm 2020). They explain the interactions of profit rates and investment, as well as the dynamics of wage increases, as inter-linked processes of turbulent equalization. The idea that both processes follow similar and at the same time very specific dynamics draw on Marx' insight that the "*competition among workers is only another form of the competition among capitalists*" (Marx 1999, 651).

These recent contributions close the gap in the literature between dynamics of competition between firms and the development of wages. However, empirical analysis in this literature is restricted to industry aggregates, and thus only average impacts. In this paper, I estimate the impact of profitability, capital intensity and cost structure on the full distribution of wage levels as well as growth rates. I find that (1) in the majority of industries, profits as well as wages exhibit turbulent equalization and (2) capital intensity and cost structure play a role in determining persistent industrial wage inequality, with substantial differences between quantiles of wage levels as well as growth rates. Finally (3), I show that lagged profit rates on new capital have a substantial positive impact on wage increases, which suggests that turbulent equalization is the link between firms' competition and workers' income inequality.

The paper is structured as follows: Section 2 discusses the literature on various dimensions of earnings inequality, its structural determinants as well as the classical political economics approach. In Section 3 I present an integrated model of firm competition, wage bargaining and emerging persistent inequalities. Section 4 introduces the data. Section 5 investigates the turbulent dynamics of profit rates and wage growth, Section 6 estimates the magnitude of industrial inequality over the full income distribution and Section 7 the impact of competition between capital on wage growth. Section 8 concludes.

2 Literature

Wage inequality is a ubiquitous companion of capitalist competition. Wages differ between occupations, but more importantly, for the same occupation between demographic groups (Mincer and Polachek 1974; Oaxaca 1973; Shaikh, Papanikolaou, and Wiener 2014), firms (Simón 2010; Song et al. 2019), industries (Krueger and Summers 1986, 1988; Gibbons and Katz 1992; Gittleman and Wolff 1993; Gittleman and Pierce 2011) and countries (Blau and Kahn 1996, 2005; Haskel and Slaughter 1998; Devroye and Freeman 2001; Simón 2010). While different dimensions of income inequality are well researched, no consensus exists about the underlying mechanisms. However, contributions from the classical political economic tradition suggest that the systematic patterns of competition, encapsulating interaction between the firms who eventually pay the wages in question, provides this link.

Persistent industry wage premiums cannot be explained by personal characteristics, skills or productivity. On the contrary, Howell (1989)'s direct comparison of individual education against production parameters (including capital intensity, profitability and market concentration) finds that its impact on inter-industry inequality is insignificant. When analysis is extended to the individual level, skill coefficients are significant but still smaller than key structural variables. Differences in skill endowments are the dominant explanation for income inequality in the neoclassical literature's labor market equilibrium models. It is noteworthy, as Simón (2010, 311) observes, that empirical evidence for these effects is not conclusive between studies. Consistent with these results, Blau and Kahn (1996)'s international comparison study finds that structural factors and residual inequality have a much larger impact than measured characteristics. These results are robust to controlling for unobserved skill differentials (Devroye and Freeman 2001) or cognitive abilities (Blau and Kahn 2005).

In contrast, institutional approaches emphasize the role of collective bargaining and legal regulations such as minimum wages (Hedström and Swedberg 1985; Blanchflower and Bryson 2002; Hirsch 2004). Their results suggest that the conditions of wage-setting are at least as important as the characteristics of wage-earners. However, even when equilibrium-based labor market models include the impact of trade unions and legal intervention (thus reflecting the institutional criticism), "residual inequality" remains the largest factor (Simón 2010, 311). In summary, institutions matter beyond setting boundaries to the relationship between individual characteristics on wages. At the same time, structural characteristics on the firm- and industry-level have a substantial impact on inter-industry wage inequality. For example, Dunlop (1948, 359) notes that a high share of labor cost in total unit cost sets effective limits to the outcomes of wage bargaining. A firm's cost structure determines how far wage increases can go before an operation can no longer withstand competition. The aforementioned Howell (1989) notes the significance of capital intensities and industry scales in explaining inequality. More recently, Blanchflower, Oswald, and Sanfey (1996) and Du Caju, Rycx, and Tojerow (2011), find a positive relationship between profitability and wage premiums, both on the industry- and firm-level.

The classical political economic approach links the relationship between structural characteristics and active wage-bargaining via the analysis of real capitalist competition. Botwinick (2018)'s seminal work derives limits to workers actively achieving wage increases from capitalists' ability to pay, which in turn are determined by excess profit margins over rivals. He uses Shaikh's (1980, 2008, 2016) model of turbulent[1] competitive dynamics between and within industries to explain persistent inter-industry wage inequalities. Mokre and Rehm (2020) expands the model to investigate the turbulent dynamics of wage increases between industries, and find a significant link between the

[1] In this literature, turbulence refers to seemingly non-stationary processes. When recurring patterns, such as equalizing processes, are called turbulent, non-stationarity occurs in combination with coherent structures, that can be analyzed statistically. The characterization of such processes is analyzed systematically in the field of fluid dynamics (Ferziger and Perić 2002, 265).

dynamics of profit rates and wage growth. This link is the key departure from both general equilibrium approaches to, and an institutional conception of, the labor market. It grounds the analysis of wage inequality in social production and reproduction.

This literature is an alternative to neoclassical general equilibrium models, where perfect competition prohibits persistent inequality (unless based in skill differentials), as well as a modification of institutional economics where institutions counteract the equalizing effect of the market. The most important stylized facts of the approach are (1) persistent inequalities between average compensation (Botwinick 2018) motivating the investigation, (2) stable distributions of wages between demographic groups and over time (Shaikh, Papanikolaou, and Wiener 2014) indicating a systematic dynamic, (3) and the turbulent equalization of wage increases (Mokre and Rehm 2020) connecting these dynamics to real competition.

In the kinetic equations literature on income inequality, individual wage growth processes can be approximated by probability distributions which, conditional on fairly basic assumptions, are stable (Gabaix 2009; Fischer 2018; Jagielski and Kutner 2019). More recently, Shaikh (2020) presents a kinetic equations model for the turbulent equalization of wages, where labor supply follows increasing wages, and subsequently depressing them again (much like capital investments do following profit rates on new capital). These results are grounded in the mathematic intution of Laplace transforms, the analytical conversion of differential equations into frequency distributions. (**???**) These techniques are out of the scope of this paper, as are their counter-parts in socio-combinatorial statistical mechanics (dos Santos 2019). However, empirical insight into the nature of the distributional properties of wages, profits, and the connection between the two are necessary to calibrate such data generating processes.

In this paper, I investigate the distributional aspects of income inequality on the employee- rather than the industrial aggregate level. This allows me to address the question whether there is a general link between profit rates and wages, or if the results are rather carried by profit-sharing within highly paid segments, eg. managers. At the same time, putting the distribution of wage incomes (albeit of a representative sample rather than the full population) at the center of the analysis is only intuitive when discussing inequality. The more detailed data allows for a more detailed investigation of the interactions between competition and inequality.

3 Model

3.1 Real Competition

The theory of real competition in classical political economics links the order of production to the perpetual attempts of profit-seeking firms to deviate from that order. (Shaikh 2016)[2]

[2] This sub-section essentially re-frames Shaikh (2016)'s theory of competition, highlighting the elements relevant for analyzing income inequality.

This is in sharp contrast to theories of perfect competition and imperfect competition alike. In the former, a competitive market is defined by firms behaving as passive price-takers, ie. the order of the system is characterized by the absence of disorder. The latter includes market power as a departure from competitive markets, ie. a tension between competitive passivity and market power-enabled active choices. However, neither makes a connection between competitive behavior and outcomes of competition. This, in contrast, is central for the real competition literature.

Within industries, firms compete for the same market, each facing a downward-sloping demand curve. Both competition and a common environment of taxation, regulation and changes in demand bind prices together, such that they move in the same direction in an equalizing fashion, but without ever settling in perfect equality.

To capture a larger market share, firms decrease their cost of production and undercut rivals' prices, which increases their own competitive space to maneuver. Competitive space between the most efficient producers and their competitors allows the former to increase their prices and thus their profit margins. When this most efficient technology is reproducible, rivals will establish similar cost structures for new capital, again reducing the competitive space and thus prices. The turbulent equalization of prices within industries is the result of perpetual price-setting below and above the general level.

The firm with the highest reproducible profit margin has the lowest production cost by definition. Because they can push prices down and act as points of attraction for rivals' investment, they are the focal points of competitive behavior, and referred to as regulating capitals. Firms employ different vintages of capital at the same time, ie. even if all capitals adopt the most efficient technology in new investment, average cost structure depends on the composition of their total operation. Due to the time dimension as well as different cost structures, the turbulent equalization of prices gives rise to persistently different average profit rates within one industry.

Between industries, firms direct their investment towards the highest profit rate on new capital. Capital is mobile between industries, and cross-industry investment is a common practice, either by buying shares of existing firms, or combining production for different markets in one corporation (Kogut and Chang 1991; Doeringer and Terkla 1995; Cavaglia and Moroz 2002). The point of attraction for new investment between industries is the capital with the highest reproducible expected profit rate, ie. the regulating capital.

Consequently, investment in industries with above-average regulating profit rates accelerates. This increases supply in this industry and reduces competitive space between low-cost producers; both factors tend to decrease prices. Falling prices leads to lower regulating profit rates and decelerating investment. The opposite dynamic arises for industries with below-average regulating profit rates.

The result is a turbulent equalization of industrial profit rates on new capital between industries, a perpetual pattern of crossing the average. However, there are persistent structural differences between industries regarding the share of capital cost in total cost, the turnover time of capital, and the combinations of capital vintages. The equalization of regulating profit rates is not only consistent with persistently different average profit rates; the turbulent dynamic of the former produce the inequalities in the latter.

3.2 Capitalist Competition and Income Inequality

Wages are determined in active bargaining between workers and capitalists. The key factors for wage growth are workers' credible threat to increase cost (through collective action or political pressure) and capitalists' ability to pay, where labor's organizational strength represents the former.

Capitalists' ability to pay depends on the profit margin in production. Capitals with the highest reproducible profit margin regulate conditions of production within one industry, and thereby average outcomes. The willingness to pay of regulating capitals depends not only on their profit margins but the ability to keep their position against the closest contenders (sub-dominant capitals), ie. the profit margin differentials between the two. This does not mean that regulating capitals must keep their advantage, actually both wage increases or cost-reducing innovations of rivals regularily dethrone market-leaders. However, remaining the most efficient capital is an important motive for firm behavior, and will affect their limits in bargaining.

Competition links the dynamics of profit rates and wages (Marx 1999, 651). Excess profit margins put pressure on rival firms as well as increase capitalists' ability to pay. Furthermore, accelerating investment in one industry acts as a point of attraction for mobile labor, primarily via the unemployed reserve army, and, in a smaller extent, by direct coaxing (Smith 1999, Chapter 10).

The concrete mechanisms of this link were also delineated in the industrial relations literature of the mid-20th century. In order to increase employment, firms in growing industries will offer higher wage rates: *"These factors require that any industry or firm which seeks to expand its employment rapidly must expect to pay a premium rate."* [Dunlop (1948); p.347] Firms in stagnating industries on the other hand will admit much lower wage growth: *"[…] a relatively stagnant industry […] would scarcely be expected to raise wages as soon, or even as far, as the progressive industries."* (Hansen 1946) Hansen and Dunlop's argument of wage increases emphasizes the role of workers demanding, and firms being able to afford, wage increases.[3]

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[3] This literature also acknowledges the ultimately cyclical patterns of expansion and productivity growth, Dunlop (1948, 348) speaks of the "life-cycles" of industries where productivity and employment increase. This is perfectly consistent with the theory of real competition: increasing productivity is the weapon of choice in within-industry competition, but also the reason why regulating profit rates fall below the average and make the "progressive" industry a relatively "stagnant" one.

3.3 Persistent Inequalities and Turbulent Equalization

Profit margins give the upper limit to wage growth, ie. the largest wage increase capitalists can afford without becoming unprofitable and be eliminated from the market. For regulating capitals, the upper limit to wage growth is such that they remain the lowest cost producer in a market, ie. excess profit margins over the closest contenders'. While these limits will hardly ever be met in actual negotiations, for the same organizational strength, bargaining outcomes will move in the same direction as the limits.

Excess profit margins are the outcome of competition within and between industries. Within an industry, average profit margins increase when regulating capitals push down cost by investing in new technology and decrease when they engage in price-cutting. Between industries, excess profit margins decrease when investment at the lowest reproducible cost accelerates, and increase when competition relaxes due to more profitable investment opportunities elsewhere. These are the core processes of turbulent equalization; the competitive limits to wage growth are governed by the same turbulent patterns.

Much like regulating and average profit rates, the turbulent equalization of wage increases gives rise to persistently different wage levels between and within industries. The persistent differences are the result of differential strength in labor organizing and differences in the capital structure.

Maximum wage growth within one industry is the profit margin (price minus unit cost) m, normalized by the labor-output requirement L/Q in Equation (1). The price-cost margin can be written as a product of the profit rate r and the capital-output requirement K/Q in Equation (2). Plugging this into (1), the upper limit is given by the product of the profit rate and the capital-labor ratio K/L, as in Equation (3). As Botwinick (2018, 212) notes, turbulent equalization of the profit rate means that persistent wage inequalities will arise from structurally different capital-labor ratios. However, it is exactly the equalization process of the profit rate that gives rise to the turbulent dynamics of wage increases; it links the competition between capitals and income inequality.

$$w'_1 = \frac{m}{L/Q} \qquad (1)$$

$$m = \frac{Y-K}{Q} = r\frac{K}{Q} \qquad (2)$$

$$w'_1 = r\frac{K}{Q}\frac{Q}{L} = r\frac{K}{L} \qquad (3)$$

Since regulating capitals govern the conditions of production within one industry, the impact of regulating profit rates on wage increases is central. The limit to their ability to pay is however bound to their sustained existence as the regulating capital, ie. producing at lower cost than their closest contender (the sub-dominant capital) (Botwinick 2018, 216). This does not imply that regulating capitals cannot be dethroned, only that their resistance to such events is an important part of their competitive strategy.

Thus, the second, more narrow limit to wage increases is given by the unit cost differentials between the regulating and sub-dominant capitals within one industry (k^* and k^s), normalized by the reulating capital's labor-output requirement, in Equation (4). It takes effect in employment by regulating capitals, but as these regulate industry outcomes, affects the whole industry.

If one compares two industries A and B with the same cost difference between regulating and subdominant capital $k^s - k^*$, and divides by each industry's regulating unit labor requirements l^*, the second limit is revealed as proportional to the ratio of unit cost to unit labor requirements k^*/l^*, as in Equation (5).

$$w'_2 = \frac{(k^s - k^*)}{(L/Q)^*} = \frac{(k^s - k^*)}{l^*} \tag{4}$$

$$\frac{(k^s - k^*)_A}{k_A^*} = \frac{(k^s - k^*)_B}{k_B^*}$$

$$\frac{\left[\frac{k^s - k^*}{l^*}\right]_A}{(k^*/l^*)_A} = \frac{\left[\frac{k^s - k^*}{l^*}\right]_B}{(k^*/l^*)_B}$$

$$\frac{\left[\frac{k^s - k^*}{l^*}\right]_A}{\left[\frac{k^s - k^*}{l^*}\right]_B} = \frac{(k^*/l^*)_A}{(k^*/l^*)_B} \tag{5}$$

As with the first limit, competition between industries and the subsequent flows of new investment ensure turbulent equalization of the competitive difference between regulating and sub-dominant capitals. The same mechanisms that give rise to persistent inter-industrial wage inequalities over time also constitute the link between the dynamics of profit rates and wages.

Shaikh (2008)'s essential insight is that the rate of profit on new capital, the regulating profit rate, is the focal point of capitalists' competitive and investment behavior. Since regulating profit rates are turbulently equalizing, its value in one year cannot explain inequalities that persist over time. Over time, structural factors in wage growth limits, ie. capital intensity and share of labor cost in total cost, arise as explanatory variables for industrial wage premiums.

This is explained by Botwinick (2018)'s insight, that competition moves the "practical limits" to active wage bargaining (see Dunlop (1948)). Then, the regulating profit rate provides the link between Marx' *"competition among workers"* and *"competition among capitalists"* and plays an important role expanding the limits to wage increases. The relationship is driven by the impact of regulating profit rates on wage increases. Indeed, Mokre and Rehm (2020) find turbulently equalizing behavior in wage growth rates, as well as positive and significant impacts of profit rates on new capitals on them.

3.4 Distributional Aspects of Real Competition

When using employee-level data, the turbulent equalization of real wage increases can be understood as movements of labor force segments along the distribution of wage growth rates, or "switching places" on the curve. For a given distribution of wage increases, one segment placing higher necessarily means that another would move down the curve. Indeed, the distribution of wage increases in the US (for full-time employment) has been of remarkably stable form since 1990 (see Figure 1). In Appendix ?? I plot fitted Laplace and Asymmetric Laplace distributions over the growth rates.

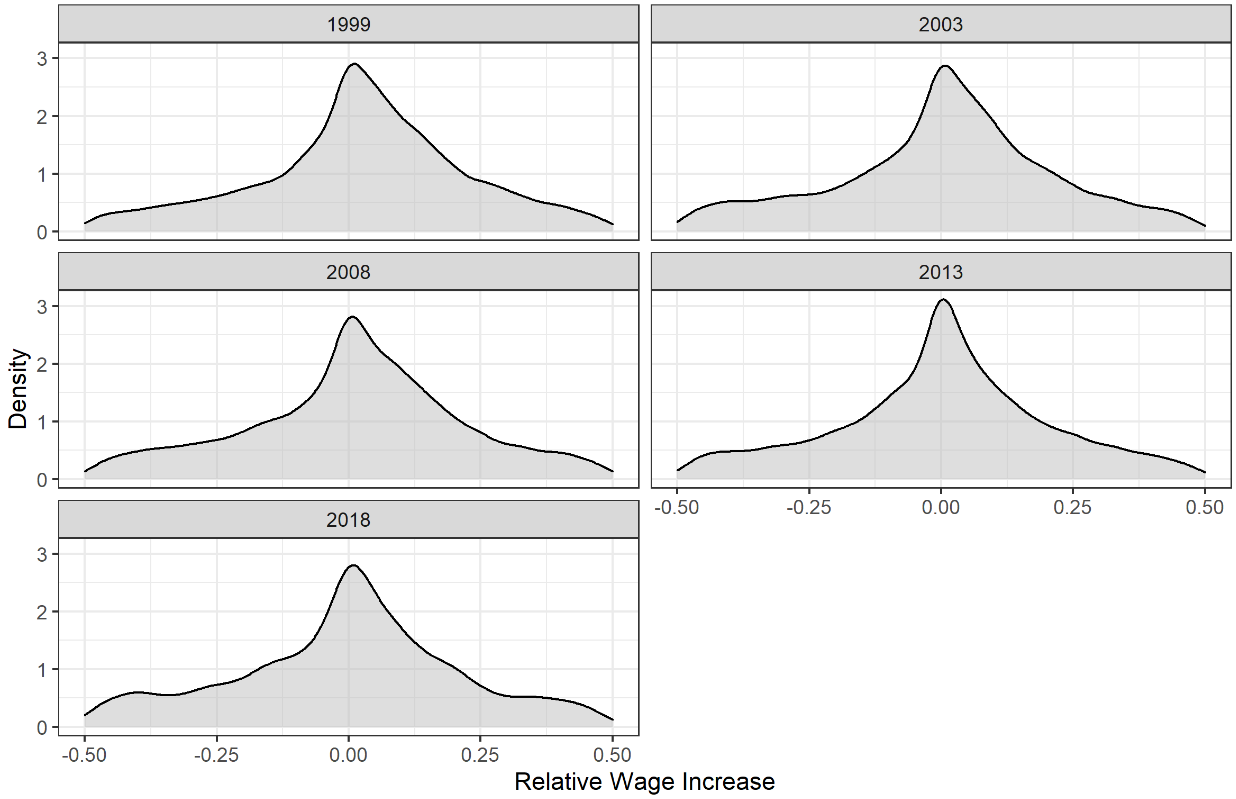

Figure 1: Distribution of Wage Growth, all observations and in 5-year-intervals. Data: CPS 1990-2018, BEA Industry Accounts 1990-2018, Own calculations and crosswalks.

The distribution of wage increases can be understood as a process of distributing aggregate wage income within the working class. It mirrors the distribution of aggregate profits in the course of establishing a general profit rate. This stochastic formulation does not imply that the bargaining success of one segment of the working class comes at the expense of others.

But there is no reason to assume that the competitive dynamics of wage growth should be the same for all segments of the working class. For example, there is little reason to believe that the relationship between negative profit rates and negative wage growth is the same as for positive values. Within the range of positive wage increases, workforces with stronger unions should be able to capitalize more on “their” capitalists’ ability to pay. They should also be able to better resist wage cuts when confronted when employers make losses. This motivates the use of conditional quantile regression (Koenker and Bassett 1978) in this paper, which estimates the impact of a change in covariates on a given percentile of the dependent variable’s distribution (I provide more detail in Section 6).

The model investigates the differential impacts of real competition on wage inequality using an employee-level micro-data set. This sheds light on the relationship between competition and inequality, and for the first time investigates the distributional aspects of this relationship. Furthermore, the results provide the basis for a systematic study of how competitive dynamics give rise to stable income distributions.

4 Data

Ideally I would observe employer-employee dynamics in a matched dataset, as in Du Caju, Rycx, and Tojerow (2011) or Song et al. (2019), to match individual wage growth, the incremental profit rate of the most efficient firm in one industry, and structural characteristics on the firm-level. As such data is not widely available, I retrieve employee-level data from the Current Population Survey's (CPS) Annual Social and Economic Supplement (ASEC) and combine them with the corresponding industrial aggregate indicators from the Bureau of Economic Analysis (BEA) industry accounts.

I restrict the sample to full-time workers that reported income from the same occupation in two consecutive years. From the CPS, I retrieve data on income, demographics (age, sex, race, education), structural factors (industry, occupation and employment conditions) and union membership. After matching this with industry level data on profits, capital intensity, cost structure, industry scale and investment (Appendix Section 11.3 details calculations and crosswalks), I calculate annual wage growth.

The sample includes between 1 and 1724, representing between 443 and 5318097 workers. In a year-industry crosstable there are only two empty cells, both from industry 486, pipeline transportation. Outside of pipeline and water transportation there is no year-industry combination with less than 5 observations.

The IPUMS CPS furthermore does not disclose extremely high incomes to prevent identification. Over the time period investigated in this paper (1998-2018), the Census Bureau applied two methods for observations above an identification treshold[4] : "replacement values" from 1996-2010, and rank proximity swapping from 2011 onwards. For the former method, researchers find observations with similar demographic characteristics like the top earner, and use their income as a replacement. They take into account gender (male or female), race (black, hispanic or "not black, not hispanic"), full time employment (equal to or exceeding 50 weeks per year, 35 hours per week). For rank proximity swapping, all values exceeding the treshold are ranked from highest to lowest, and systematically swapped within a bounded interval. (IPUMS 2020)

I prefer the data output produced by these methods over "top coded" survey (where observations above the treshold are just replaced by the treshold), as the distribution of the distorted data should better resemble the real distribution than properly right-hand censored data. Both the replacement values and rank swapping method should also preserve

[4] for the wage income variable INCWAGE, the replacement treshold was USD 25 000 between 1998-2002, USD 35 000 from between 2003-2010, USD 47 000 between 2011-2014, USD 56 000 in 2015 and USD 55 000 from 2016 onwards

some of the relationship between demographic characteristics and income data. However, one must understand that this censoring of the data will make the results of my investigation less reliable in the top deciles.

The merged dataset, reduced to full time workers and cleaned of any observations for which I could not calculate wage growth or allocate the corresponding industry level structural data, consists of 245314 observations over 21 years, 52 NAICS industry subsectors and 86 ISCO job categories (at the two digit level). Considering observation weights, this represents 429 million persons, between 16 and 43 million per year.

Table 1 reports summary statistics for each year and NAICS industry, both in terms of observations in the dataset, and using corresponding survey weights. For 75 % of the cells, I have more than 48 observations. Table 2 gives an overview of the demographic and unionization details. It is noteworthy that for a large majority of observations, union membership is not surveyed ("not in universe").

Table 1: Observations per NAICS Industry Subsector and Year

	Mean	SD	Min	25th Percentile	Median	75th Percentile	Max
Observations	225	297	1	48	123	253	1 724
Weighted	393 246	544 240	443	77 106	202 875	429 310	5 318 097

Table 2: Demographic and workplace condition distributions. Data: CPS 1990-2018, BEA Industry Accounts 1990-2018, Own calculations and crosswalk.

	Observations	Weighted	%
Race			
Non-White	35 639	57 118 025	13
White	209 675	371 913 282	87
Gender			
Female	102 365	180 537 666	42
Male	142 949	248 493 641	58
Union			
No Union Coverage	234 795	410 766 432	96
Union Coverage	10 519	18 264 875	4

Table 3 reports summary statistics for the two key variables, year-to-year wage growth on the individual and incremental profit rates on the industry level. While there are large outliers, which I eliminate before the empirical investigation, 50 % of the wage growth observations are between -13 % and 27 %. For incremental profit rates, the center 50 % of the observations lie between -6 % and 22 %. As I am investigating income inequality, I compare quantiles weighted by the numer of full time equivalent employees in a year and industry, which gives a weighted center 50 % between -1 % and 20 %. For the empirical investigation, I eliminate all observations with wage growth lowar than -50 % or higher than 50 %.

Figures 2 and 3 plot the probability density functions of these two variables. For wage increases, extra plots are included to show the different locations but similar distributional shapes between genders and race categories. For incremental profit rates, I separately plot the distribution for each 1-digit NAICS sector category and reveals somwhat similar ranges but substantially different shapes.

Table 3: Wage Growth and Incremental Profit Rates. Data: CPS 1990-2018, BEA Industry Accounts 1990-2018, Own calculations and crosswalks. Wage growth weighted by CPS-ASEC survey weights, incremental profit rates weighted by industrial fixed assets.

	Mean	Min	25th %	50th %	75th %	Max
Wage Growth Rate	1.67	-1.00	-0.13	0.04	0.27	61345.20
Incremental Profit Rate	0.07	-2.65	-0.02	0.06	0.18	2.28

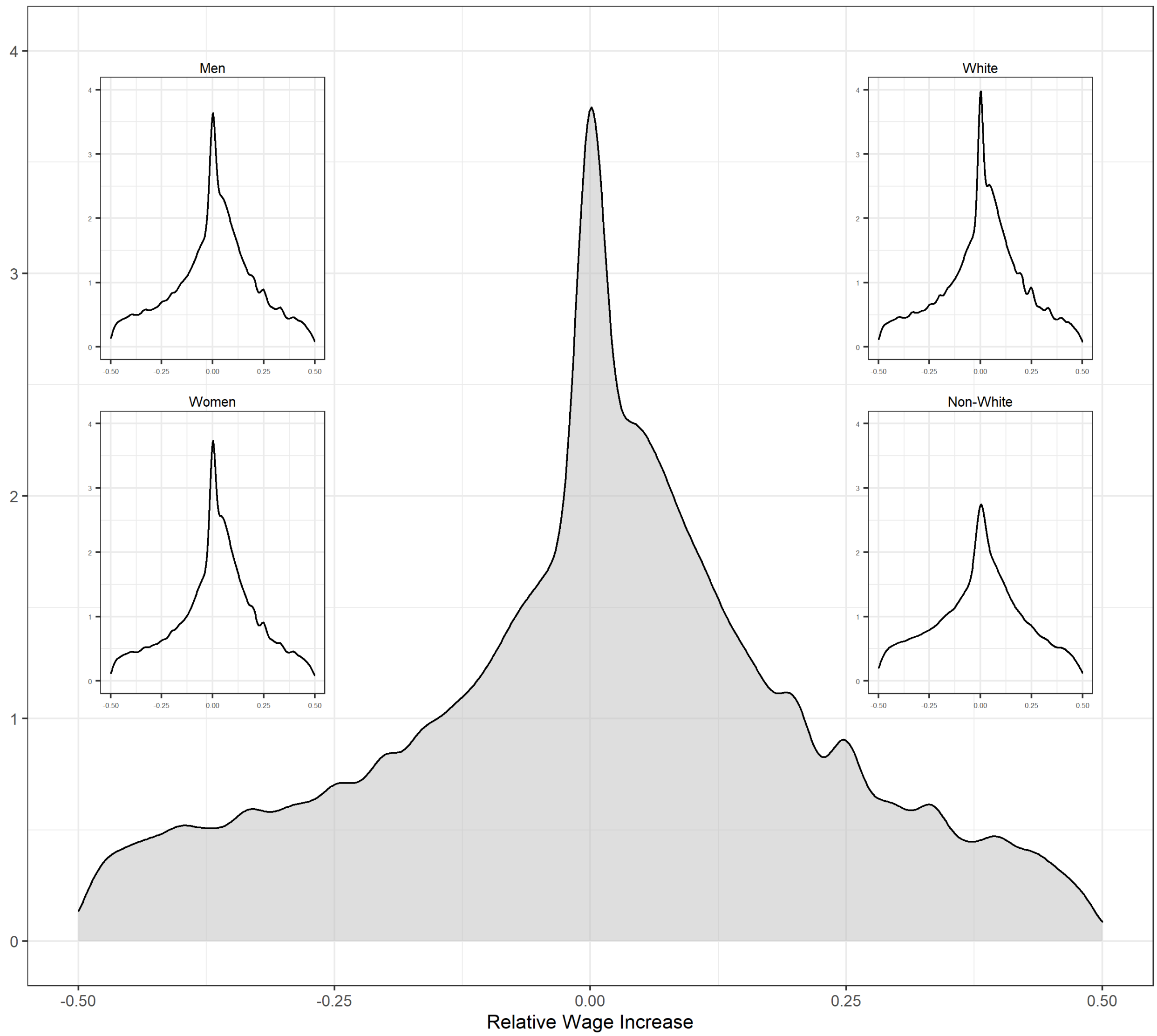

Figure 2: Distribution of Wage Growth, all observations and by demographic categories. Data: CPS 1990-2018, BEA Industry Accounts 1990-2018, Own calculations and crosswalks.

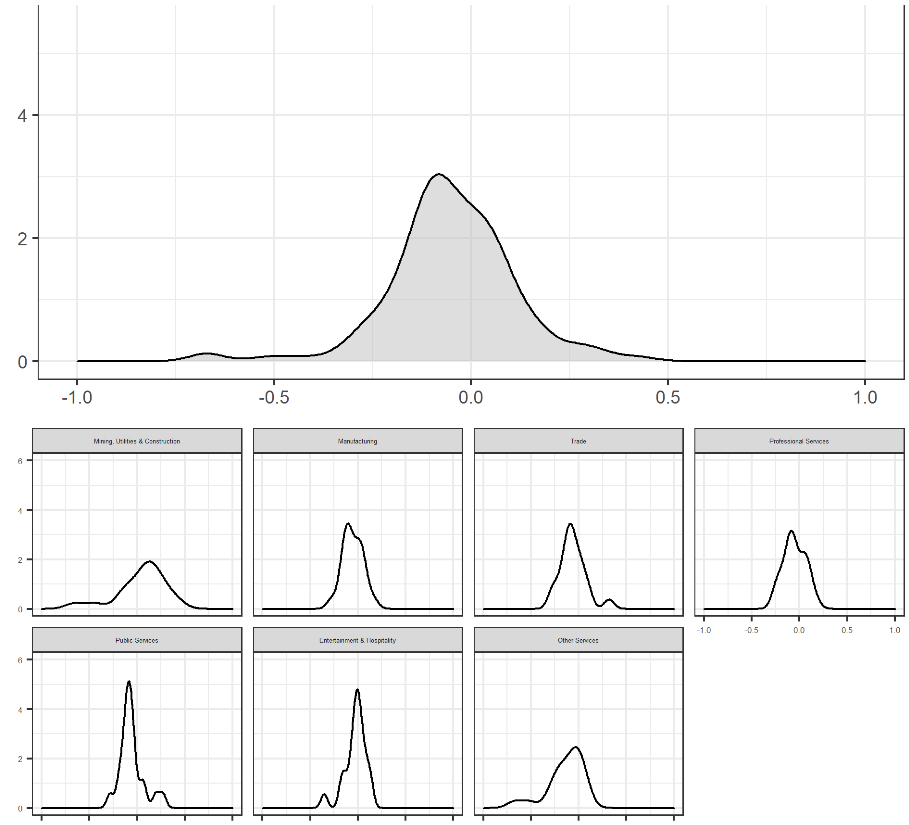

Figure 3: Data: CPS 1990-2018, BEA Industry Accounts 1998-2018, Own calculations and crosswalks.

5 Regulating Profit Rates and Wage Increases are Turbulently Equalizing

Competition can be understood as the deviation of single agents from established price or cost levels, in order to increase the rate of return on new operations. The ubiquitous disorder only establishes order and gives rise to characteristic patterns of turbulent equalization. Turbulently equalizing processes, eg. of product prices between competitors, do not imply equality but rather movements around a common center of gravitation, eg. the general price level.

Shaikh (2008) calls industrial profit rates equalizing if incremental rates of return are found on both sides of the weighted average rate between industries approximately half of the time each. Ferziger and Perić (2002)’s definition of turbulence (in fluid flows) includes seemingly random (non-stationary) development over time as well as coherent structures, ie. repeating events that can be statistically analyzed. Vaona (2011) presents an econometric model for turbulent equalization of profit rates building on Mueller (1986).

They argue that a variable $x_{i,t}$ participates in turbulent equalization if it is gravitating around or converging to a cross-sectional general value. The variable is said to be gravitating if its deviation from the cross-sectional mean $\tilde{x}_{i,t} = x_{i,t} - \overline{x}_t$ cannot be predicted by a non-linear transformation of the time trend nor a fixed intercept term. This means that one cannot predict if the variable will be higher or lower than the cross-sectional average. The process is called converging if the time trend can explain its trajectory, but no fixed intercept term remains. If the intercept term represents persistent differences of the variable from the cross-sectional average, convergence implies that such a "bias" exists, but wears off over time.

I model return rates as a non-linear product of the time trend after allowing for serial correlation in the error term (i.e. a moving average set-up). Note that the dependent variable in the setup is the deviation from the annual weighted average $\tilde{x}_{i,t}$. I estimate the coefficients in an ordinary linear regression using Maximum Likelihood (as the moving average term does not allow for analytical solution) (Gardner, Harvey, and Phillips 1980).

$$\tilde{x}_{i,t} = \alpha_i + \frac{\beta_1}{t} + \frac{\beta_2}{t^2} + \frac{\beta_3}{t^3} + \epsilon_{i,t} \qquad (6)$$
$$\epsilon_{i,t} = \rho_i \epsilon_{i,t-1} + \xi_{i,t} \qquad (7)$$

A process is called gravitating if none of the parameters α, β are significantly different from zero, and converging if the intercept term α is not significantly different from zero. It is called not turbulently equalizing when the intercept is significantly different from zero, i.e. there is a persistent deviation of realizations of the variable from the annual weighted average. I use a Student-t test, to detect significant deviations from zero.

Table 4 reports the p-values of Student t-tests for insignificance on each of the coefficients as well as the concluding behavior for incremental profit rates in 53 industries. The results suggest gravitation in incremental profit rates in 41 and convergence in 3 industries. Incremental profit rates are turbulently equalizing in all but 9 industries.

Table 5 summarizes the results for industry level growth rates of average full time equivalent employee compensation. I find no evidence against gravitating wage increases in 30 and with regards to convergence in 4 industries. Wage increases are turbulently equalizing in all but 19 industries. This number is marginally higher than the one in Mokre and Rehm (2020), where a Wald test is performed for gravitation, but auto-correlation in the error term is not included, to find turbulent equalization in 31 out of 46 industries.

The t-statistic is not available (NA) for some entries. This is due to the fact that the moving average term is estimated by maximum likelihood, which might not converge. In these cases, I re-run the estimation with fewer transformations of the time trend. Consequently, I cannot test for gravitation in Vaona (2011)'s methodology in these cases, but test for convergence instead.

As I am investigating the impacts of real competition in this paper, I only use observations from all industries that participate in turbulent equalization of both profit rates and wage growth. This leaves 26 out of 53 industries in which both profit rates and wage increases are turbulently equalizing, which leaves 245314 observations. That is approximately 81 % of the original sample.

I eliminate the remaining industries, where either profit rates or wage growth do not turbulently equalize, from the sample. It is noteworthy that I find turbulent equalization of profit rates in substantially more industries, than I find it for wage growth. The precise reasons for that are a fruitful field for further investigation, but one reason might be that the mobility of labor is a slower process than the direction of new investment. Since out data only stretches over 20 years, the number of industries in which these rates gravitate around or converge to the weighted mean might be larger.

Table 4: Turbulent Behavior of NAICS industry summary level incremental profit rates. Data: BEA Industry Accounts, 1990-2018.

Industry	p-value Intercept	$\frac{1}{T}$	$\frac{1}{T^2}$	$\frac{1}{T^3}$	Turbulent Behavior
Farms	0.03	0.04	0.05	0.06	no equalization
Forestry, fishing, and related activities	0.19	0.17	0.11	0.07	gravitation
Oil and gas extraction	0.48	0.36	0.31	0.31	gravitation
Mining, except oil and gas	0.29	0.35	0.42	0.50	gravitation
Support activities for mining	0.01	0.02	0.06	0.12	no equalization
Utilities	0.00	0.00	0.00	0.00	gravitation
Construction	0.07	0.06	0.06	0.07	gravitation
Food and beverage and tobacco products	0.17	0.13	0.10	0.08	gravitation
Textile mills and textile product mills	0.18	0.13	0.10	0.09	gravitation
Apparel and leather and allied products	0.25	0.19	0.13	0.09	gravitation
Wood products	1.00	1.00	1.00		convergence
Paper products	0.00	0.00	0.00	0.00	no equalization
Printing and related support activities	0.00	0.12			no equalization
Petroleum and coal products	0.17	0.11	0.06	0.04	convergence
Chemical products	0.21	0.22	0.23	0.26	gravitation
Plastics and rubber products	0.02	0.01	0.01	0.01	no equalization
Nonmetallic mineral products	0.92	0.80	0.68	0.60	gravitation
Primary metals	0.31	0.19	0.11	0.06	gravitation
Fabricated metal products	0.13	0.12	0.12	0.14	gravitation
Machinery	0.19	0.24	0.29	0.37	gravitation
Computer and electronic products	0.40	0.31	0.28	0.24	gravitation
Electrical equipment, appliances, and components	0.54	0.53	0.52	0.51	gravitation
Motor vehicles, bodies and trailers, and parts	0.66	0.72	0.79	0.86	gravitation
Furniture and related products	0.63	0.67	0.73	0.79	gravitation
Miscellaneous manufacturing	0.87	0.86	0.84	0.83	gravitation
Wholesale trade	0.00	0.00	0.00	0.00	gravitation
Retail trade	0.95	0.85	0.63	0.49	gravitation
Air transportation	0.00	0.00	0.00		no equalization
Railroad transportation	0.06	0.08	0.11	0.14	gravitation
Water transportation	0.58	0.64	0.69	0.72	gravitation
Truck transportation	0.01	0.02	0.07	0.18	no equalization
Transit and ground passenger transportation	0.06	0.05	0.05	0.07	convergence
Pipeline transportation	0.24	0.15	0.09	0.07	gravitation
Other transportation and support activities	0.03	0.03	0.03	0.03	no equalization
Warehousing and storage	0.21	0.31	0.40	0.49	gravitation
Publishing industries (includes software)	0.55	0.47	0.42	0.38	gravitation

Motion picture and sound recording industries	0.79	0.75	0.67	0.59	gravitation
Broadcasting and telecommunications	0.82	0.77	0.74	0.70	gravitation
Information and data processing services	0.04	0.03	0.01	0.01	no equalization
Miscellaneous professional, scientific, and technical services	0.91	0.91	0.96	0.99	gravitation
Computer systems design and related services	0.88	0.80	0.72	0.63	gravitation
Administrative and support services	0.41	0.36	0.32	0.30	gravitation
Waste management and remediation services	0.91	0.96	0.97	0.89	gravitation
Educational services	0.37	0.37	0.35	0.34	gravitation
Ambulatory health care services	0.82	0.86	0.90	0.93	gravitation
Hospitals	0.84	0.85	0.81	0.79	gravitation
Nursing and residential care facilities	0.53	0.52	0.48	0.47	gravitation
Social assistance	0.15	0.12	0.12	0.13	gravitation
Performing arts, spectator sports, museums, and related activities	0.72	0.64	0.59	0.57	gravitation
Amusements, gambling, and recreation industries	1.00	1.00	1.00	1.00	gravitation
Accommodation	0.55	0.32	0.17	0.09	gravitation
Food services and drinking places	0.65	0.76	0.87	0.97	gravitation
Other services, except government	1.00	1.00	1.00	1.00	gravitation

Table 5: Turbulent Behavior of NAICS industry summary level growth rates of full time equivalent employee compensation. Data: BEA Industry Accounts, 1990-2018.

Industry	p-value Intercept	$\frac{1}{T}$	$\frac{1}{T^2}$	$\frac{1}{T^3}$	Turbulent Behavior
Farms	1.00	1.00	1.00	1.00	gravitation
Forestry, fishing, and related activities	0.01	0.02	0.04	0.10	no equalization
Oil and gas extraction	0.08	0.13	0.20	0.26	gravitation
Mining, except oil and gas	0.00	0.01	0.04	0.14	no equalization
Support activities for mining	0.29	0.51	0.82	0.88	gravitation
Utilities	0.77	0.63	0.49	0.34	gravitation
Construction	0.79	0.79	0.79	0.81	gravitation
Food and beverage and tobacco products	0.52	0.44	0.42	0.41	gravitation
Textile mills and textile product mills	0.46	0.46	0.49	0.52	gravitation
Apparel and leather and allied products	0.00	0.00	0.00	0.00	no equalization
Wood products	0.00	0.00	0.00	0.00	no equalization
Paper products	0.71	0.62	0.61	0.61	gravitation
Printing and related support activities	0.02	0.02	0.03	0.04	no equalization
Petroleum and coal products	0.99	0.79	0.57	0.41	gravitation
Chemical products	0.00	0.01	0.02	0.03	no equalization
Plastics and rubber products	0.62	0.53	0.47	0.41	gravitation
Nonmetallic mineral products	0.00	0.00	0.01	0.02	no equalization
Primary metals	0.00	0.00	0.00	0.00	no equalization
Fabricated metal products	0.33	0.25	0.22	0.18	gravitation
Machinery	0.31	0.39	0.47	0.54	gravitation
Computer and electronic products	0.00	0.00	0.00		no equalization
Electrical equipment, appliances, and components	0.15	0.19	0.24	0.29	gravitation
Motor vehicles, bodies and trailers, and parts	0.00	0.00	0.00	0.00	convergence
Furniture and related products	0.00	0.00	0.00	0.00	no equalization
Miscellaneous manufacturing	0.70	0.82	0.97	0.91	gravitation
Wholesale trade	0.00	0.00			no equalization

Retail trade	0.68	0.56	0.75		convergence
Air transportation	0.00	0.00	0.00		convergence
Railroad transportation	0.39	0.33	0.26	0.23	gravitation
Water transportation	0.05	0.07	0.10	0.15	no equalization
Truck transportation	0.22	0.35	0.52	0.67	gravitation
Transit and ground passenger transportation	0.01	0.02	0.06	0.12	no equalization
Pipeline transportation	0.00	0.00	0.00	0.00	gravitation
Other transportation and support activities	0.58	0.32	0.21	0.15	gravitation
Warehousing and storage	0.97	0.66	0.46	0.31	gravitation
Publishing industries (includes software)	0.21	0.02	0.00	0.00	no equalization
Motion picture and sound recording industries	0.40	0.60	0.80	1.00	gravitation
Broadcasting and telecommunications	0.13	0.11	0.09	0.07	gravitation
Information and data processing services	0.41	0.99	0.49	0.20	gravitation
Miscellaneous professional, scientific, and technical services	0.07	0.05	0.03		no equalization
Computer systems design and related services	0.01	0.01	0.00	0.00	no equalization
Administrative and support services	0.03	0.02	0.02	0.01	no equalization
Waste management and remediation services	0.22	0.24	0.25		convergence
Educational services	0.21	0.27	0.36	0.45	gravitation
Ambulatory health care services	0.54	0.45	0.47	0.50	gravitation
Hospitals	0.29	0.17	0.09	0.05	gravitation
Nursing and residential care facilities	0.16	0.12	0.11	0.11	gravitation
Social assistance	0.05	0.03	0.03	0.03	no equalization
Performing arts, spectator sports, museums, and related activities	0.32	0.30	0.30	0.32	gravitation
Amusements, gambling, and recreation industries	0.57	0.52	0.51	0.49	gravitation
Accommodation	0.58	0.60	0.65	0.71	gravitation
Food services and drinking places	0.02	0.02	0.03	0.05	no equalization
Other services, except government	0.12	0.17	0.24	0.31	gravitation

6 Persistent Wage Inequalities Between Industries

As discussed in the literature review in section 2, the phenomenon of demographically very similar persons, in the very same occupations but earning very different income is incongruous with ideas of labor market equilibrium. In Section 5 I found that the vast majority of industries participate in turbulent equalization of profit rates and wage growth, which is consistent with real competition.

In this section, I investigate persistent wage inequalities between industries and the impact of structural variables on industrial wage premiums. I first present the magnitude of industrial wage premiums over the full income distribution. In a second step, I estimate the impact of key structural variables, such as gross output (capturing demand effects), profits (reflecing rent-sharing), capital-intensity and the share of labor cost in total cost on individual wages.

The latter two capture the competitive restrictions to wage growth in Botwinick (2018). In both regressions, I control for gender, race and unionization to make sure the results are robust to adverse selection. Furthermore, I include ISCO occupation codes (two digits aggregation) and time.

I use conditional quantile regression (Koenker and Bassett 1978) at all 10 % quantiles of the wage distribution $\tau \in Q = (0.1, 0.2, \dots, 0.9)$. In CQR, coefficients capture the marginal effect of a covariate on a person's income at a certain point on the income distribution, conditional on that person observing this change in covariates. This is in contrast to unconditional quantile regression (Firpo, Fortin, and Lemieux 2009), which captures the impact of the overall distribution of one covariate (eg. the share of unionized workers) on a given percentile of the overall income distribution. As I want to understand the wage differentials between industries at different quantiles of the income distribution, CQR is the appropriate method.

Equation (8) lists the dependent variable and covariates in the conditional quantile regression I perform to retrieve industry wage premiums, ie. coefficients $\beta_{i,tau}$, after controlling for occupation, year, union membership, gender and race.

$$
\begin{aligned}
\hat{q}_\tau(INCWAGE_i) \quad &= \alpha_1 + \alpha_{2,o} OCC_i + \alpha_{3,t} YEAR_i + \beta_i NAICS07_i + \\
&+ \zeta UNION_i + \eta_1 GENDER_i + \eta_2 AGE_i + \eta_3 RACE_i + \eta_4 EDUC_i + \epsilon_i \ , \\
&\tau \in Q = (0.1, 0.2, \dots, 0.9) \qquad (8)
\end{aligned}
$$

Figure 4 plots the coefficients for each industry. Table 11 in Appendix 9 reports the full list of coefficients. In the regression, I omit the structural factors so as to measure the full extent of industrial inequality in the first step. For clarity the plot only shows the 20th, 50th and 80th percentile. Consistent with the literature, industrial wage inequality is substantial and persistent, with coefficients ranging from -11885 to 39460.

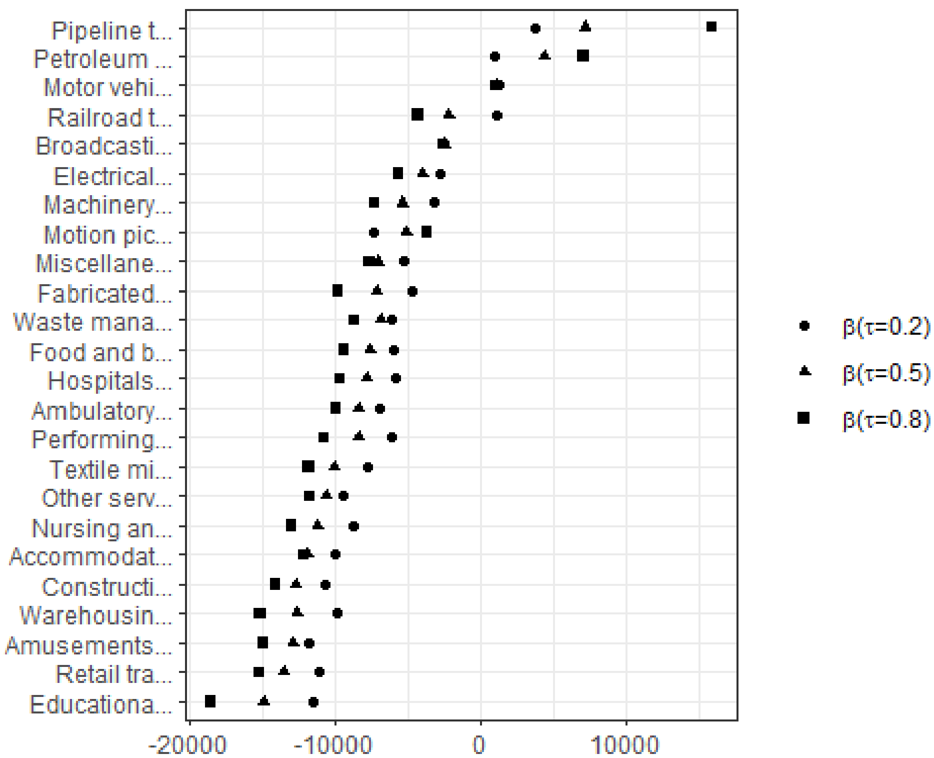

Figure 4: Wage Premiums, ie. Conditional Quantile Regression Intercept Terms, for NAICS07 Industries which participate in tubrulent equalizatioin of incremental profit rates as well as wage increases.

The theory of competition-regulated wage bargaining discussed in Section (model-persistent-turbulent) states that the same industries pay wage premiums to lower and higher income workers. As an alternative hypothesis, some industries may pay higher wages to the top layer of their employees, while others offer better conditions to nearly-minimum wage workers. This would indicate a more complex relationship between competitive factors and inter-industry wage inequality. To investigate this, I retrieve coefficients at the 20th, 50th and 80th percentiles and rank the NAICS industries accordingly (with 1 denoting the industry with the lowest wage premium, and so on). Table 6 reports the correlation between percentile rankings of industrial wage premiums. The results suggest a stable structure of industrial income inequality over the distribution, ie. the same industries paying relatively high wages to their lowest and highest earners.

Table 6: Correlation between industry wage premiums magnitudes at percentiles 0.2, 0.5 and 0.8. Data: IPUMS CPS, Full Time Employees, 1998-2018.

	$\beta_{\tau=0.2}$	$\beta_{\tau=0.5}$	$\beta_{\tau=0.8}$
$\beta_{\tau=0.2}$	1.0000	0.9165	0.8243
$\beta_{\tau=0.5}$	0.9165	1.0000	0.9696
$\beta_{\tau=0.8}$	0.8243	0.9696	1.0000

In a second regression, adding sturctural variables on the industrial level (capital intensity CL, share of labor cost in total cost SLTC, gross output GO and gross profits PRO) allows me to test key results from Botwinick (2018) (see Equation (9). To investigate the long-term effects of the structural characteristics, I do not control for industry NAICS in this setup. Figure 5 plots the coefficients for all 10 % quantiles, with shades indicating significance levels. Table 7 reports the coefficients for the 20th, 50th and 80th percentile including different categories of race and education. I present the full results for all 10 % quantiles in Appendix Table 9.

$$\begin{aligned} \hat{q}_\tau(INCWAGE_i) \quad &= \alpha_1 + \alpha_{2,o}OCC_i + \alpha_{3,t}YEAR_i + \\ &+\zeta_1 log(CL) + \zeta_2 log(SLTC) + \zeta_3 log(GO) + \zeta_4 PRO \\ &+\zeta UNION_i + \eta_1 GENDER_i + \eta_2 AGE_i + \eta_3 RACE_i + \eta_4 EDUC_i + \epsilon_i\text{", "} \\ &\tau \in Q = (0.1,0.2,\ldots,0.9) \qquad (9) \end{aligned}$$

Male and unionized workers have significantly larger wage levels at all percentiles of the income distribution. Furthermore, age has a positive impact in all quantiles. While the wage premium of unionization remains approximately constant through the lower 60 % before decreasing for higher wages, the coefficients for men and age increase monotonously over the income distribution.

The capital-labor ratio has a significant, substantial and positive impact on wage levels, with an inverted U-shape over percentiles. The share of labor cost in total cost has a negative impact, which becomes more accentuated with increasing wages.

The positive coefficients of gross output have an inverted U-shape in the lower 70 % of the distribution and peaks for the 40 % percentile at USD 750, suggesting that a 100 % increase in industry demand would increase a worker's yearly wage income by that sum. The coefficients for profits (ie. gross operating surplus) are negative for all but the highest quantile.[5]

The results show that inter-industrial wage inequality is persistent, substantial and consistent over the income distribution. I also find that structural factors play an important role in explaning wage levels, but their impacts differ between percentiles. This again emphasizes the importance of distributional analysis for understanding income inequality.

Finally, there is broad agreement between my empirical results and the literature on the impact of competition on inequality. As in Botwinick (2018)'s theory of real competition limits to wage growth their role in persistent inequality.

When profit rates on new capital turbulently equalize, a larger capital intensity implies that firms can admit larger wage increases per workers over time. Capital intensity as a persistent

[5] Profits enter the regression in Billions USD because the possible negativity of operating surplus prohibits using a logarithmic scale, which explains the different scales in coefficients.

limit to wage growth is derived from competition between industries, and the empirical effect is largest closely around the median.

Conversely, a higher share of labor cost in total cost means that the same wage poses a higher danger for a regulating capital to become less cost efficient than their closest rivals. The effect comes from competition between firms within one industry for the position of regulating capital, and the negative coefficient becomes more negative, ie. has a more important impact, with each decile. This suggests that the ability of firms with a lower share of labor cost in total cost to over-pay (or give in to higher demands) is especially important for high earners.

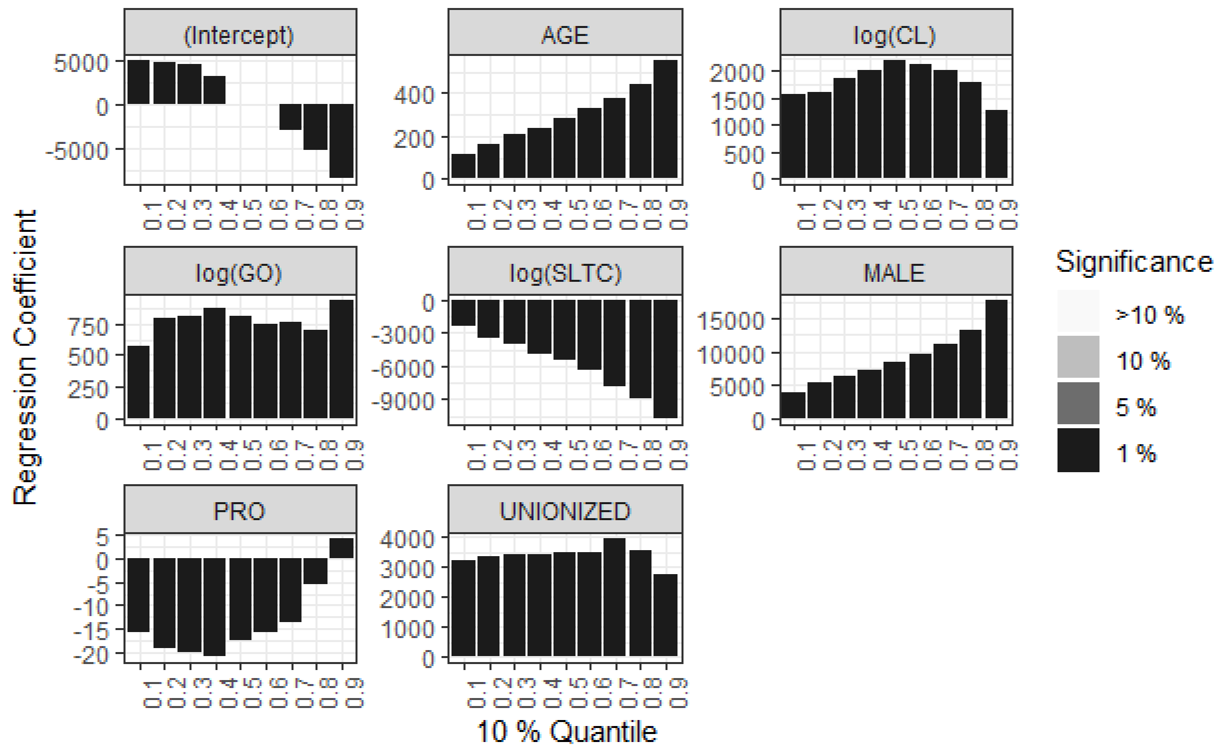

Figure 5: Coefficients for Structural Variables on the Industrial Level in Conditional Quantile Regression of Wage Levels. Data: IPUMS CPS, Full Time Employees, and BEA Industry Accounts, 1998-2018.

Table 7: Demographic and Structural Coefficients as well as p-values in Quantile Regression of Wage Levels at percentiles 0.2, 0.5 and 0.8. Data: IPUMS CPS, Full Time Employees and BEA Industry Accounts, 1998-2018.

	$\beta_{\tau=0.2}$	P	$\beta_{\tau=0.5}$	P	$\beta_{\tau=0.8}$	P
(Intercept)	4813.28	0.00	877.96	0.30	-5176.92	0.00
log(CL)	1623.00	0.00	2186.15	0.00	1793.64	0.00
log(SLTC)	-3511.68	0.00	-5547.11	0.00	-8974.22	0.00
PRO	-19.23	0.00	-17.78	0.00	-5.70	0.00
log(GO)	794.26	0.00	805.06	0.00	701.65	0.00
UNIONIZED	3325.95	0.00	3509.72	0.00	3576.98	0.00
MALE	5236.04	0.00	8302.42	0.00	13129.90	0.00

AGE	164.22	0.00	278.65	0.00	442.09	0.00
factor(RACE)200	-2414.82	0.00	-2692.09	0.00	-2879.20	0.00
factor(RACE)300	-2887.62	0.00	-3334.81	0.00	-3734.57	0.00
factor(RACE)650	-1172.85	0.00	-1716.84	0.00	102.86	0.79
factor(RACE)651	-1198.23	0.00	1044.12	0.00	2130.20	0.00
factor(RACE)652	968.55	0.01	511.91	0.28	3110.10	0.00
factor(RACE)801	-568.73	0.17	528.73	0.32	-5929.10	0.00
factor(RACE)802	-1389.67	0.00	-2870.82	0.00	-4814.52	0.00
factor(RACE)803	1138.16	0.02	466.88	0.45	-1189.53	0.20
factor(RACE)804	2830.83	0.03	1898.87	0.26	8675.03	0.00
factor(RACE)805	-37.29	0.96	-4010.83	0.00	-6190.46	0.00
factor(RACE)806	388.62	0.70	-8443.45	0.00	-8495.61	0.00
factor(RACE)807	-1371.02	0.71	5495.19	0.24	-5413.23	0.45
factor(RACE)808	-113.68	0.96	3791.91	0.15	-6682.54	0.09
factor(RACE)809	-2444.37	0.24	1290.65	0.62	-2301.07	0.56
factor(RACE)810	-4901.31	0.00	-3752.89	0.01	-6716.29	0.00
factor(RACE)811	21571.08	0.00	10268.15	0.00	20845.42	0.00
factor(RACE)812	-11269.07	0.31	-12008.78	0.40	-9074.85	0.67
factor(RACE)813	2299.15	0.43	191.81	0.96	2084.02	0.71
factor(RACE)814	29517.51	0.01	23196.38	0.11	13694.20	0.53
factor(RACE)817	36253.51	0.00	20434.08	0.04	-3176.81	0.84
factor(RACE)820	9163.42	0.03	3198.83	0.55	28934.26	0.00
factor(RACE)830	5837.63	0.19	-1947.88	0.73	7577.28	0.38
factor(EDUC99)4	2267.97	0.00	2896.73	0.00	6471.63	0.00
factor(EDUC99)5	2886.97	0.00	4122.52	0.00	6243.04	0.00
factor(EDUC99)6	4218.74	0.00	5899.90	0.00	8875.91	0.00
factor(EDUC99)7	5434.56	0.00	6960.66	0.00	10675.71	0.00
factor(EDUC99)8	5016.67	0.00	7895.17	0.00	11538.03	0.00
factor(EDUC99)9	6136.37	0.00	8911.23	0.00	12913.90	0.00
factor(EDUC99)10	8334.96	0.00	12081.20	0.00	16749.46	0.00
factor(EDUC99)11	10699.51	0.00	16110.60	0.00	22772.87	0.00
factor(EDUC99)13	11454.81	0.00	17123.33	0.00	24252.05	0.00
factor(EDUC99)14	12262.83	0.00	18271.71	0.00	25775.99	0.00
factor(EDUC99)15	18148.55	0.00	27631.83	0.00	39820.57	0.00
factor(EDUC99)16	27766.75	0.00	39676.61	0.00	54210.31	0.00
factor(EDUC99)17	32834.31	0.00	60417.63	0.00	99274.06	0.00
factor(EDUC99)18	35986.33	0.00	56436.02	0.00	84725.71	0.00

7 Quantile Impacts of Real Competition

Finally, I investigate the impact of real competition on wage growth. First and foremost, I want to understand the impact of regulating profit rates, current and lagged, on wage growth, as both variables participate in turbulent equalization. As in Section 6, conditional quantile regression is the appropriate method as I seek to understand the relationship between regulating profit rates and wage growth conditional on the industry they are observed in. The quantiles represent differences between negative and positive wage growth, as well as between moderate and large changes. In Equation (10) I include all demographic, structural, time, industry and occupation controls as in Equation (9) and introduce the incremental profit rate for periods t, and $t-1$. In Appendix Section 10 I also present results from alternative specifications with more lags of the incremental profit rate, against which the results are robust.

$$
\begin{aligned}
\hat{q}_\tau(\Delta INCWAGE_i) \quad & = \alpha_1 + \alpha_{2,o}OCC_i + \alpha_{3,t}YEAR_i + \alpha_{4,i}NAICS07_i + \\
& +\beta_1 IPR_t + \beta_2 IPR_{t-1} + \beta_3 log(CL) + \beta_4 log(SLTC) + \beta_5 PRO + \beta_6 log(GO) \\
& +\zeta UNION_i + \eta_1 GENDER_i + \eta_2 AGE_i + \eta_3 RACE_i + \eta_4 EDUC_i + \epsilon_i\ , \\
& \tau \in Q = (0.1, 0.2, \ldots, 0.9) \qquad (10)
\end{aligned}
$$

Figure 6 plots the coefficients for incremental profit rates, current and in two lags, as well as the capital-labor ratio and the share of labor cost in total unit cost. I omit quantile coefficients from the plot if they are not significantly different from zero at the 5 % level. Table 8 reports coefficients and p-values for the 20th, 50th and 80th quantiles. Full results are printed in Appendix Table 10.

Current incremental profit rates have an insignificant impact on the middle of the distribution (20 % through 70 % quantiles), but are positive in the 10th and negative in the 80th and 90th percentile. This is different from the results in Mokre and Rehm (2020), but can be explained by the fast alternation of above- and below-average regulating profit rates - if it takes one or two years for the effect on wages to materialize, the corresponding industry would already be pushed below the average again.

Consistent with this rationale, lagged regulating profit rates have a significant and positive impact on wage growth which outweighs the negative coefficient of current RPRs at all quantiles. Lagged regulating profit rates are 1 % significant and positive on all percentiles, except at the median where the coefficient is signifcant only at the 10 % level. A U-shape of quantile coefficients over the income distribution is noticeable.

The coefficients for the first lag lie between 0.0013 and 0.0091. For comparison, in the Mokre and Rehm (2020) study, the first lag coefficient is 0.0119. A coefficient of 0.009 implies that a 100 percentage point increase in regulating profit rates means that the corresponding wage increase would be 0.9 percentage points higher, which is a substantial effect given that the median wage increase in the sample stands at 4 %. The 75 % percentile (ie. third quantile) of incremental profit rates is 19.28 %, which would translate into almost 0.2 percentage points of additional wage growth.

Except for the 90 % quantile, the share of labor cost in total unit cost has a negative impact on wage growth, as expected. This is in line with Botwinick (2018)'s theoretical argument. The coefficients of the capital-labor ratio are positive as expected, but are not significantly different from zero at most percentiles. However, since the coefficients and significance levels are unambiguous in the wage levels regression of Section 6, Botwinick's assertion that the factor plays an important role in persistent inequalities appears to hold over time. Furthermore, both gross output (industry size) and profits are insignificant over most quantiles, and have negative coefficients where they are significant.

As expected, unionization has a positive impact on wage growth at all but the highest percentile. At the same time, men seem to experience lower wage growth (keeping in mind the considerable wage level bonus I find earlier). This would fit a "catching-up" (or "catchingdown") dynamic between men's and women's full-time wages in the United States. The same inverse relationship between coefficients in the level and the growth rate regression hold for age.

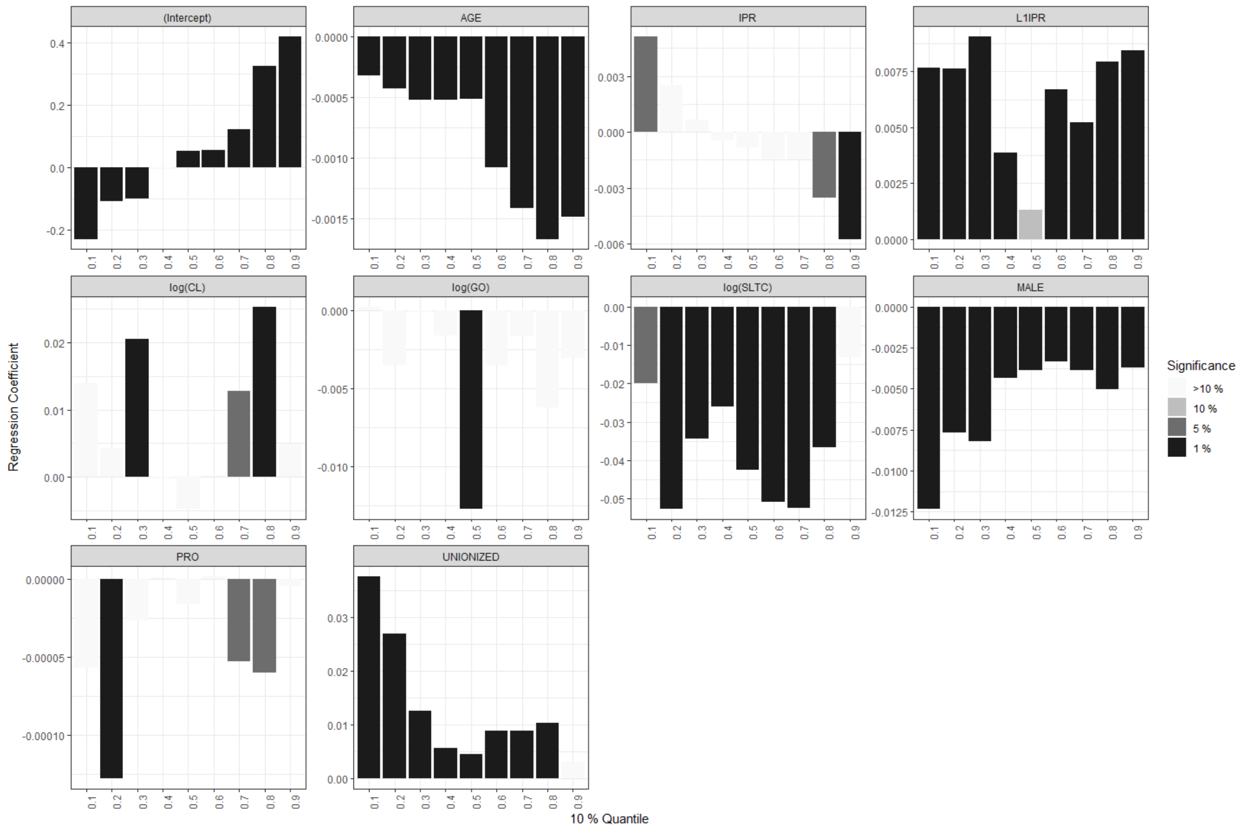

Figure 6: Conditional Quantile Regression, Impacts of Demographic and Structural Factors on year-to-year Wage Increases.

Table 8: Conditional Quantile Regression, Impacts of Demographic and Structural Factors on year-to-year Wage Increases.

	$\beta_{\tau=0.2}$	P	$\beta_{\tau=0.5}$	P	$\beta_{\tau=0.8}$	P
(Intercept)	-0.1101	0.0061	0.0535	0.0002	0.3251	0.0000
IPR	0.0025	0.2199	-0.0009	0.2554	-0.0035	0.0328
L1IPR	0.0077	0.0002	0.0013	0.0827	0.0079	0.0000
log(CL)	0.0043	0.6301	-0.0047	0.1392	0.0254	0.0003
log(SLTC)	-0.0526	0.0000	-0.0426	0.0000	-0.0366	0.0000
PRO	-0.0001	0.0003	0.0000	0.2148	-0.0001	0.0334
log(GO)	-0.0035	0.5218	-0.0127	0.0000	-0.0062	0.1563
UNIONIZED	0.0269	0.0000	0.0045	0.0000	0.0103	0.0000
MALE	-0.0077	0.0000	-0.0039	0.0000	-0.0051	0.0000
AGE	-0.0004	0.0000	-0.0005	0.0000	-0.0017	0.0000
factor(RACE)200	-0.0541	0.0000	-0.0099	0.0000	0.0060	0.0003

In Section 5, I found that both regulating profit rates and wage growth rates are turbulently equalizing in the majority of industries, which employ about 81 % of the full-time working population. This supports the hypothesis that the dynamics of real competition govern both investment and the results of wage bargaining in large parts of the US economy.

Section 6 found persistent industrial wage inequality and substantial impacts of the capital labor-ratio , as well as of the share of labor cost in total cost on all percentiles of the wage distribution. This supports that persistent industrial inequality is partially explained by competitive dynamics. Distributional analysis indicates that the importance of within-industry competition, which materializes in the share of labor cost in total cost, is more important for higher-earning quantiles. Conversely, the capital-labor ratio coefficient peaks at the median which indicates, which indicates that between-industry competition is more important for "normal" wage levels than for segments affected by legal wage floors or quasi-managerial profit sharing.

The results in this section emphasize the impact of turbulent equalization of profit rates between industries on wage growth. Furthermore, I find limited support for structural limits to wage growth on the individual level. The results hold on almost all 10 % quantiles, but indicate a stark difference between negative and positive wage growth as well as between small and large increases. This shows again the importance of a distributional analysis of wage levels and growth rates.

8 Conclusion

In this paper, I argued that wage inequality between industries is largely the consequence of competition between capitals. Movements of labor and wages depend on the dynamics of investment and profit rates, both of which behave in a turbulent fashion. While wages are set in direct and confrontational bargaining between labor and capital, wage growth is restricted by capitals' ability to pay. This implies a concurrent link between profit rates on new capital and wage increases, which Mokre and Rehm (2020) showed to be positive and substantial on the aggregate level.

The findings are consistent with Shaikh (2020)'s model of turbulently equalizing wages, in which he argues that workers move towards sectors which pay above-average wages, thereby depressing the wage rates by increased labor supply, and inducing a subsequent exodus into other sectors. However, I argue that higher wages are offered due to the dynamics of wage bargaining, where the limits to increases are determined by firms' ability to pay. My model provides an explanation for the driving force behind the turbulent dynamic in firms' competitive behavior. This is also a possible explanation for Marx' assertion that "*the competition among workers is only another form of the competition among capitalists*" (Marx 1999, p651).

I applied conditional quantile regression analysis to investigate (1) industrial wage inequality at different points of the income distribution and (2) differential impacts of regulating profit rates on wage increases. The results show persistent industrial wage premiums and a significant impact of the capital-labor ratio and the share of labor cost in total cost on these. The order of industrial wage premiums is stable between quantiles, ie. industries paying higher wages to their top earners also admit wage premiums to the lower layer of their workforce. While the structural impact of the capital-labor ratio is positive and the share of labor costs in total cost has a negative impact over the full distributions, the coefficients are substantially different between quantiles. This is broadly consistent with the predictions in the classical political economic literature on persistent inequalities.

Furthermore, I am able to show a stable positive impact of the regulating profit rates in the first and second lag on wage increases. While the current incremental profit rate has a no significant impact over most of the distribution and ambiguous signs for the lowest 10 % and highest 20 %, its effect is substantially outweighed by its lag, which is consistent with a delay between investment and wage increases. Again, coefficients vary substantially over the distribution. The results is robust to including more lags or different structural variables. The coefficients are close to the ones known from aggregate analysis, and support the hypothesis of turbulent equalization as the link between firm competition and income inequality.

This paper generalizes the results of Botwinick (2018) and Mokre and Rehm (2020), further investigating the role of real competition in income inequality. It emphasizes the need for distributional analysis, and provides a possible explanations for the well-known but not fully understood mechanisms giving rise to wage inequality. The results refute the suspicion that aggregate results could be carried by profit-sharing with quasi-managerial positions. They also provide a basis for the investigation of modeling the dynamics behind income inequality drawing on the full distribution of wages and profits.

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Appendix A

Tables 9 and 10 present the full results for structural and demographic coefficients at all 9 quantiles of the conditional quantile regression of wage levels and wage growth respectively. Table 11 reports the industry coefficients β from Equation (8) for all deciles $\tau \in Q = (0.1, 0.2, \ldots, 0.9)$.

Table 9: Demographic and Structural Coefficients and p-values in Quantile Regression of Wage Levels at deciles 0.1 through 0.9. Data: IPUMS CPS, Full Time Employees, 1990-2018.

	$\beta_{\tau=0.1}$	P	$\beta_{\tau=0.2}$	P	$\beta_{\tau=0.3}$	P	$\beta_{\tau=0.4}$	P	$\beta_{\tau=0.5}$	P	$\beta_{\tau=0.6}$	P	$\beta_{\tau=0.7}$	P	$\beta_{\tau=0.8}$	P	$\beta_{\tau=0.9}$	P
(Intercept)	5004.25	0.00	4813.28	0.00	4757.41	0.00	3263.19	0.00	877.96	0.30	-593.38	0.52	-2764.89	0.01	-5176.92	0.00	-8413.49	0.00
log(CL)	1584.88	0.00	1623.00	0.00	1869.21	0.00	2030.65	0.00	2186.15	0.00	2124.07	0.00	2013.04	0.00	1793.64	0.00	1286.29	0.00
log(SLTC)	-2478.18	0.00	-3511.68	0.00	-4085.79	0.00	-4866.31	0.00	-5547.11	0.00	-6391.76	0.00	-7808.02	0.00	-8974.22	0.00	-10675.32	0.00
PRO	-15.71	0.00	-19.23	0.00	-20.19	0.00	-21.03	0.00	-17.78	0.00	-15.89	0.00	-13.68	0.00	-5.70	0.00	4.27	0.00
log(GO)	573.20	0.00	794.26	0.00	807.05	0.00	868.91	0.00	805.06	0.00	746.83	0.00	762.69	0.00	701.65	0.00	941.97	0.00
UNIONIZED	3215.39	0.00	3325.95	0.00	3432.22	0.00	3452.74	0.00	3509.72	0.00	3459.88	0.00	3946.41	0.00	3576.98	0.00	2735.94	0.00
MALE	3937.57	0.00	5236.04	0.00	6247.28	0.00	7172.79	0.00	8302.42	0.00	9560.19	0.00	11073.09	0.00	13129.90	0.00	17766.29	0.00
AGE	112.07	0.00	164.22	0.00	205.38	0.00	239.08	0.00	278.65	0.00	325.24	0.00	376.41	0.00	442.09	0.00	548.03	0.00
factor(RACE)200	-2240.06	0.00	-2414.82	0.00	-2567.12	0.00	-2658.99	0.00	-2692.09	0.00	-2611.03	0.00	-2704.03	0.00	-2879.20	0.00	-3017.82	0.00
factor(RACE)300	-2517.92	0.00	-2887.62	0.00	-2936.12	0.00	-3230.07	0.00	-3334.81	0.00	-3659.12	0.00	-2278.08	0.00	-3734.57	0.00	-3868.13	0.00
factor(RACE)650	-865.28	0.00	-1172.85	0.00	-1365.35	0.00	-1290.49	0.00	-1716.84	0.00	-1159.86	0.00	-326.41	0.31	102.86	0.79	976.40	0.08
factor(RACE)651	-757.45	0.00	-1198.23	0.00	-257.01	0.01	91.88	0.41	1044.12	0.00	1261.66	0.00	1799.25	0.00	2130.20	0.00	3290.41	0.00
factor(RACE)652	1914.28	0.00	968.55	0.01	874.95	0.03	231.29	0.59	511.91	0.28	1955.16	0.00	2150.67	0.00	3110.10	0.00	1944.01	0.06
factor(RACE)801	-826.45	0.08	-568.73	0.17	-1548.07	0.00	-902.97	0.07	528.73	0.32	200.17	0.73	-2238.43	0.00	-5929.10	0.00	-1436.71	0.22
factor(RACE)802	-2901.02	0.00	-1389.67	0.00	-2432.54	0.00	-2432.17	0.00	-2870.82	0.00	-3065.79	0.00	-3115.09	0.00	-4814.52	0.00	-5924.09	0.00
factor(RACE)803	-2769.80	0.00	1138.16	0.02	1163.92	0.03	215.72	0.71	466.88	0.45	2022.21	0.00	2182.16	0.00	-1189.53	0.20	-4629.28	0.00
factor(RACE)804	-2918.20	0.05	2830.83	0.03	559.28	0.70	-567.42	0.71	1898.87	0.26	2323.79	0.20	5686.61	0.01	8675.03	0.00	11781.48	0.00
factor(RACE)805	1566.43	0.08	-37.29	0.96	627.12	0.48	-1013.89	0.28	-4010.83	0.00	-3752.49	0.00	-1020.03	0.42	-6190.46	0.00	-9273.36	0.00
factor(RACE)806	4929.36	0.00	388.62	0.70	-2952.09	0.01	-6268.83	0.00	-8443.45	0.00	-10692.33	0.00	-8976.19	0.00	-8495.61	0.00	5600.51	0.05
factor(RACE)807	-14090.77	0.00	-1371.02	0.71	11119.47	0.01	8704.68	0.05	5495.19	0.24	2487.33	0.62	-1046.81	0.86	-5413.23	0.45	-12960.51	0.21
factor(RACE)808	2155.79	0.35	-113.68	0.96	9915.97	0.00	12412.73	0.00	3791.91	0.15	-5260.11	0.06	-7703.90	0.02	-6682.54	0.09	-15816.82	0.01
factor(RACE)809	-20.53	0.99	-2444.37	0.24	-2832.34	0.22	-2385.73	0.32	1290.65	0.62	1367.85	0.63	-622.04	0.85	-2301.07	0.56	-7629.55	0.18
factor(RACE)810	-2736.55	0.02	-4901.31	0.00	-3663.45	0.00	-3349.00	0.01	-3752.89	0.01	-2232.37	0.13	-1489.01	0.38	-6716.29	0.00	-10059.02	0.00
factor(RACE)811	17785.70	0.00	21571.08	0.00	17249.32	0.00	13742.23	0.00	10268.15	0.00	35714.27	0.00	28822.64	0.00	20845.42	0.00	5411.51	0.50
factor(RACE)812	-7457.79	0.55	-11269.07	0.31	-15057.39	0.22	-13978.85	0.28	-12008.78	0.40	-3670.66	0.81	-6425.17	0.72	-9074.85	0.67	-12755.76	0.68
factor(RACE)813	-4526.74	0.17	2299.15	0.43	1100.45	0.73	-154.12	0.96	191.81	0.96	-1002.63	0.80	-463.38	0.92	2084.02	0.71	12018.82	0.14
factor(RACE)814	33800.02	0.01	29517.51	0.01	26993.77	0.03	24833.38	0.06	23196.38	0.11	21131.97	0.17	18250.18	0.31	13694.20	0.53	6819.60	0.83
factor(RACE)817	43692.74	0.00	36253.51	0.00	31046.22	0.00	26173.82	0.01	20434.08	0.04	14281.44	0.19	7097.89	0.58	-3176.81	0.84	-15415.56	0.49
factor(RACE)820	3361.98	0.47	9163.42	0.03	7323.33	0.11	5660.88	0.25	3198.83	0.55	3256.30	0.57	7999.98	0.23	28934.26	0.00	75556.92	0.00
factor(RACE)830	11978.87	0.02	5837.63	0.19	1085.30	0.83	-2793.24	0.60	-1947.88	0.73	5143.69	0.41	2228.72	0.76	7577.28	0.38	-1460.03	0.91
factor(EDUC99)4	3828.98	0.00	2267.97	0.00	1860.22	0.01	1803.73	0.02	2896.73	0.00	3751.55	0.00	4591.24	0.00	6471.63	0.00	5648.73	0.00
factor(EDUC99)5	3657.21	0.00	2886.97	0.00	2443.66	0.00	2304.61	0.00	4122.52	0.00	4829.11	0.00	5073.96	0.00	6243.04	0.00	4722.35	0.01
factor(EDUC99)6	5146.83	0.00	4218.74	0.00	3966.81	0.00	4143.43	0.00	5899.90	0.00	6863.26	0.00	7106.99	0.00	8875.91	0.00	8268.69	0.00
factor(EDUC99)7	5682.08	0.00	5434.56	0.00	4893.30	0.00	5270.70	0.00	6960.66	0.00	7974.17	0.00	8799.89	0.00	10675.71	0.00	10666.88	0.00
factor(EDUC99)8	5011.22	0.00	5016.67	0.00	5217.90	0.00	5913.91	0.00	7895.17	0.00	9056.21	0.00	9873.00	0.00	11538.03	0.00	10967.45	0.00
factor(EDUC99)9	6107.14	0.00	6136.37	0.00	5812.35	0.00	6747.41	0.00	8911.23	0.00	10345.84	0.00	11999.55	0.00	12913.90	0.00	13626.00	0.00
factor(EDUC99)10	8014.61	0.00	8334.96	0.00	8849.65	0.00	9742.25	0.00	12081.20	0.00	13618.71	0.00	14755.75	0.00	16749.46	0.00	17078.27	0.00
factor(EDUC99)11	9680.54	0.00	10699.51	0.00	11528.40	0.00	13098.85	0.00	16110.60	0.00	18114.45	0.00	19938.85	0.00	22772.87	0.00	24805.64	0.00
factor(EDUC99)13	10383.11	0.00	11454.81	0.00	12497.57	0.00	14191.55	0.00	17123.33	0.00	19228.37	0.00	21336.14	0.00	24252.05	0.00	26888.98	0.00

factor(EDUC99)14	10969.60	0.00	12262.83	0.00	13222.18	0.00	14911.44	0.00	18271.71	0.00	20844.52	0.00	22732.61	0.00	25775.99	0.00	28422.61	0.00
factor(EDUC99)15	15348.03	0.00	18148.55	0.00	20601.65	0.00	23245.20	0.00	27631.83	0.00	31492.49	0.00	34833.49	0.00	39820.57	0.00	46232.52	0.00
factor(EDUC99)16	23182.52	0.00	27766.75	0.00	30655.44	0.00	34365.51	0.00	39676.61	0.00	44502.26	0.00	48268.09	0.00	54210.31	0.00	61001.71	0.00
factor(EDUC99)17	26152.94	0.00	32834.31	0.00	40353.69	0.00	50756.56	0.00	60417.63	0.00	71912.09	0.00	85164.33	0.00	99274.06	0.00	145671.97	0.00
factor(EDUC99)18	31491.04	0.00	35986.33	0.00	42166.30	0.00	49247.93	0.00	56436.02	0.00	64604.38	0.00	72476.08	0.00	84725.71	0.00	108788.43	0.00

Table 10: Conditional Quantile Regression, Impacts of Demographic and Structural Factors on year-to-year Wage Increases.

	$\beta_{\tau=0.1}$	P	$\beta_{\tau=0.2}$	P	$\beta_{\tau=0.3}$	P	$\beta_{\tau=0.4}$	P	$\beta_{\tau=0.5}$	P	$\beta_{\tau=0.6}$	P	$\beta_{\tau=0.7}$	P	$\beta_{\tau=0.8}$	P	$\beta_{\tau=0.9}$	P
(Intercept)	-0.2297	0.0000	-0.1101	0.0061	-0.0995	0.0004	-0.0068	0.7061	0.0535	0.0002	0.0536	0.0082	0.1210	0.0000	0.3251	0.0000	0.4180	0.0000
IPR	0.0051	0.0396	0.0025	0.2199	0.0007	0.6491	-0.0005	0.6186	-0.0009	0.2554	-0.0015	0.1633	-0.0015	0.2282	-0.0035	0.0328	-0.0057	0.0081
L1IPR	0.0077	0.0021	0.0077	0.0002	0.0091	0.0000	0.0039	0.0000	0.0013	0.0827	0.0067	0.0000	0.0052	0.0000	0.0079	0.0000	0.0084	0.0001
log(CL)	0.0140	0.1882	0.0043	0.6301	0.0206	0.0008	-0.0002	0.9563	-0.0047	0.1392	0.0003	0.9454	0.0128	0.0140	0.0254	0.0003	0.0049	0.5944
log(SLTC)	-0.0199	0.0376	-0.0526	0.0000	-0.0343	0.0000	-0.0261	0.0000	-0.0426	0.0000	-0.0508	0.0000	-0.0523	0.0000	-0.0366	0.0000	-0.0131	0.1165
PRO	-0.0001	0.1835	-0.0001	0.0003	0.0000	0.2798	0.0000	0.9476	0.0000	0.2148	0.0000	0.9289	-0.0001	0.0114	-0.0001	0.0334	0.0000	0.9070
log(GO)	0.0002	0.9722	-0.0035	0.5218	-0.0001	0.9690	-0.0016	0.5107	-0.0127	0.0000	-0.0035	0.2087	-0.0017	0.5991	-0.0062	0.1563	-0.0031	0.5959
UNIONIZED	0.0375	0.0000	0.0269	0.0000	0.0126	0.0000	0.0057	0.0000	0.0045	0.0000	0.0089	0.0000	0.0089	0.0000	0.0103	0.0000	0.0031	0.1981
MALE	-0.0123	0.0000	-0.0077	0.0000	-0.0082	0.0000	-0.0044	0.0000	-0.0039	0.0000	-0.0033	0.0000	-0.0039	0.0000	-0.0051	0.0000	-0.0037	0.0027
AGE	-0.0003	0.0000	-0.0004	0.0000	-0.0005	0.0000	-0.0005	0.0000	-0.0005	0.0000	-0.0011	0.0000	-0.0014	0.0000	-0.0017	0.0000	-0.0015	0.0000
factor(RACE)200	-0.0484	0.0000	-0.0541	0.0000	-0.0417	0.0000	-0.0235	0.0000	-0.0099	0.0000	-0.0091	0.0000	0.0018	0.1442	0.0060	0.0003	0.0156	0.0000
factor(RACE)300	-0.0193	0.0157	-0.0463	0.0000	-0.0400	0.0000	-0.0289	0.0000	-0.0128	0.0000	-0.0068	0.0440	0.0045	0.2526	0.0139	0.0088	0.0452	0.0000
factor(RACE)650	0.0342	0.0006	0.0128	0.1244	0.0041	0.4809	0.0022	0.5583	0.0021	0.4969	0.0108	0.0099	0.0141	0.0041	0.0312	0.0000	0.0412	0.0000
factor(RACE)651	-0.0277	0.0000	-0.0356	0.0000	-0.0224	0.0000	-0.0081	0.0000	-0.0065	0.0000	-0.0029	0.0595	0.0083	0.0000	0.0159	0.0000	0.0187	0.0000
factor(RACE)652	0.0111	0.3981	0.0060	0.5795	-0.0011	0.8876	0.0023	0.6378	0.0166	0.0000	0.0318	0.0000	0.0436	0.0000	0.0501	0.0000	0.0291	0.0109
factor(RACE)801	0.0026	0.8644	-0.0060	0.6334	-0.0445	0.0000	-0.0219	0.0001	0.0063	0.1696	0.0228	0.0003	0.0280	0.0002	0.0329	0.0011	-0.0123	0.3530
factor(RACE)802	0.0208	0.0637	0.0140	0.1326	-0.0044	0.4954	-0.0069	0.0979	0.0007	0.8395	0.0088	0.0630	0.0071	0.1979	0.0165	0.0261	0.0096	0.3240
factor(RACE)803	0.0319	0.1293	0.0167	0.3417	-0.0354	0.0036	-0.0004	0.9582	0.0023	0.7216	-0.0056	0.5264	0.0016	0.8758	-0.0159	0.2565	-0.0129	0.4815
factor(RACE)804	-0.0100	0.8740	-0.0011	0.9827	0.0141	0.6991	0.0139	0.5533	0.0091	0.6326	-0.0156	0.5549	-0.0400	0.1940	-0.0713	0.0880	-0.0346	0.5282
factor(RACE)805	0.0555	0.0457	-0.0149	0.5198	-0.0031	0.8460	-0.0028	0.7900	0.0103	0.2218	0.0056	0.6309	-0.0099	0.4680	0.0118	0.5224	0.0589	0.0153
factor(RACE)806	-0.1953	0.0000	0.0798	0.0086	0.0715	0.0007	0.0012	0.9304	-0.0188	0.0874	-0.0709	0.0000	0.0166	0.3542	0.0558	0.0212	-0.0294	0.3565
factor(RACE)807	-0.1415	0.2635	-0.2848	0.0069	-0.3633	0.0000	-0.4200	0.0000	-0.4379	0.0000	-0.4777	0.0000	-0.0190	0.7595	-0.0897	0.2857	-0.2019	0.0676
factor(RACE)808	-0.1246	0.0607	-0.1774	0.0013	-0.0804	0.0363	-0.1080	0.0000	-0.1269	0.0000	-0.1669	0.0000	0.0701	0.0312	0.0093	0.8339	-0.0887	0.1262
factor(RACE)809	0.0261	0.7337	0.0422	0.5086	0.0341	0.4414	0.0135	0.6377	-0.0075	0.7445	0.0565	0.0796	0.0542	0.1494	0.0397	0.4359	0.0910	0.1739
factor(RACE)810	0.0862	0.0205	-0.0323	0.2970	-0.0302	0.1604	-0.0303	0.0295	-0.0306	0.0064	-0.0381	0.0148	-0.0310	0.0893	-0.0225	0.3624	-0.0299	0.3573
factor(RACE)811	0.2628	0.0046	0.1481	0.0555	0.1102	0.0401	0.0417	0.2295	0.0009	0.9755	0.0930	0.0172	0.0451	0.3213	-0.0166	0.7883	-0.1300	0.1087
factor(RACE)812	-0.0181	0.9625	-0.1111	0.7293	-0.2180	0.3281	-0.2883	0.0452	-0.3352	0.0040	-0.0725	0.6548	-0.0210	0.9114	-0.0889	0.7285	0.1094	0.7451
factor(RACE)813	-0.1571	0.1274	-0.1522	0.0763	-0.0709	0.2341	-0.0020	0.9580	0.0103	0.7399	-0.0172	0.6923	-0.0395	0.4338	-0.0724	0.2898	-0.0396	0.6599
factor(RACE)814	0.4227	0.2473	0.2906	0.3397	0.2022	0.3387	0.1615	0.2366	0.1376	0.2124	0.0970	0.5282	0.0549	0.7591	-0.0145	0.9524	-0.1290	0.6860
factor(RACE)817	0.4254	0.1010	0.3190	0.1399	0.2341	0.1187	0.1756	0.0699	0.1508	0.0543	0.1200	0.2713	0.0687	0.5887	0.0047	0.9783	-0.0718	0.7511
factor(RACE)820	-0.0641	0.6587	-0.1974	0.1025	-0.2690	0.0014	-0.0876	0.1061	-0.0180	0.6817	-0.0125	0.8378	0.0671	0.3454	0.0817	0.3969	-0.0192	0.8798
factor(RACE)830	0.1222	0.4046	0.0242	0.8427	-0.0712	0.4009	-0.1642	0.0027	-0.0343	0.4389	-0.0314	0.6107	0.0027	0.9699	-0.0652	0.5031	-0.1645	0.1986
factor(EDUC99)4	-0.0809	0.0036	-0.0601	0.0093	0.0008	0.9589	-0.0547	0.0000	-0.0174	0.0381	-0.0174	0.1362	-0.0124	0.3624	-0.0838	0.0000	-0.0551	0.0229
factor(EDUC99)5	-0.0701	0.0067	-0.0625	0.0037	-0.0118	0.4316	-0.0364	0.0002	0.0009	0.9102	-0.0052	0.6309	-0.0282	0.0256	-0.0948	0.0000	-0.0642	0.0044
factor(EDUC99)6	-0.0416	0.1124	-0.0400	0.0671	0.0105	0.4904	-0.0121	0.2164	0.0054	0.4951	0.0011	0.9170	-0.0171	0.1825	-0.0737	0.0000	-0.0348	0.1285
factor(EDUC99)7	-0.0435	0.0926	-0.0475	0.0275	0.0030	0.8399	-0.0203	0.0358	0.0063	0.4179	0.0039	0.7178	-0.0316	0.0125	-0.1143	0.0000	-0.0755	0.0008
factor(EDUC99)8	-0.0544	0.0352	-0.0486	0.0239	0.0036	0.8089	-0.0263	0.0064	0.0039	0.6204	-0.0007	0.9499	-0.0212	0.0935	-0.0924	0.0000	-0.0699	0.0020
factor(EDUC99)9	-0.0801	0.0023	-0.0444	0.0423	0.0097	0.5226	-0.0216	0.0279	0.0045	0.5733	-0.0019	0.8653	-0.0296	0.0216	-0.1155	0.0000	-0.0927	0.0001
factor(EDUC99)10	-0.0408	0.1071	-0.0304	0.1485	0.0259	0.0766	-0.0060	0.5260	0.0099	0.1934	0.0060	0.5717	-0.0200	0.1070	-0.0989	0.0000	-0.0697	0.0016
factor(EDUC99)11	-0.0266	0.2940	-0.0157	0.4577	0.0405	0.0057	0.0037	0.6992	0.0152	0.0470	0.0120	0.2608	-0.0189	0.1269	-0.1007	0.0000	-0.0718	0.0012

factor(EDUC99)13	-0.0344	0.1754	-0.0140	0.5077	0.0415	0.0047	0.0045	0.6330	0.0143	0.0620	0.0106	0.3228	-0.0219	0.0781	-0.1019	0.0000	-0.0669	0.0026
factor(EDUC99)14	-0.0168	0.5096	-0.0110	0.6021	0.0434	0.0031	0.0042	0.6577	0.0150	0.0513	0.0086	0.4234	-0.0228	0.0672	-0.1018	0.0000	-0.0822	0.0002
factor(EDUC99)15	-0.0160	0.5285	0.0003	0.9871	0.0531	0.0003	0.0094	0.3206	0.0167	0.0292	0.0101	0.3456	-0.0238	0.0550	-0.1124	0.0000	-0.0844	0.0001
factor(EDUC99)16	0.0033	0.8950	0.0109	0.6063	0.0643	0.0000	0.0149	0.1161	0.0204	0.0077	0.0129	0.2265	-0.0243	0.0504	-0.1180	0.0000	-0.0956	0.0000
factor(EDUC99)17	-0.0464	0.0720	-0.0235	0.2741	0.0418	0.0050	0.0104	0.2786	0.0153	0.0493	0.0015	0.8913	-0.0357	0.0047	-0.1005	0.0000	-0.0664	0.0032
factor(EDUC99)18	-0.0242	0.3445	-0.0039	0.8558	0.0525	0.0004	0.0138	0.1498	0.0158	0.0410	0.0071	0.5084	-0.0284	0.0236	-0.1102	0.0000	-0.0860	0.0001
factor(NAICS07)23	0.0006	0.9883	-0.0254	0.4770	0.0477	0.0544	-0.0133	0.4051	0.0029	0.8222	0.0215	0.2337	0.0835	0.0001	0.1363	0.0000	0.0287	0.4441

Table 11: Industry Wage Premiums at Percentiles 0.3, 0.5 and 0.7. Data: IPUMS CPS, Full Time Employees, 1990-2018

	$\beta_{\tau=0.1}$	S.E.	$\beta_{\tau=0.2}$	S.E.	$\beta_{\tau=0.3}$	S.E.	$\beta_{\tau=0.4}$	S.E.	$\beta_{\tau=0.5}$	S.E.	$\beta_{\tau=0.6}$	S.E.	$\beta_{\tau=0.7}$	S.E.	$\beta_{\tau=0.8}$	S.E.	$\beta_{\tau=0.9}$	S.E.
Construction	-9257.70	0.00	-9089.11	0	-10663.27	0	-11750.92	0.00	-12710.67	0	-13326.82	0	-14094.74	0	-14306.53	0.00	-13319.38	0
Food and beverage and tobacco products	-4613.13	0.00	-4798.07	0	-6044.64	0	-6678.00	0.00	-7634.78	0	-8318.55	0	-9430.02	0	-10133.63	0.00	-10423.23	0
Textile mills and textile product mills	-6195.89	0.00	-6420.97	0	-7807.72	0	-8840.50	0.00	-10025.49	0	-11073.03	0	-11838.28	0	-12638.20	0.00	-14709.56	0
Petroleum and coal products	-103.02	0.69	954.75	0	965.65	0	1956.00	0.00	4406.73	0	5977.68	0	7090.55	0	11023.53	0.00	13831.86	0
Fabricated metal products	-3272.50	0.00	-3541.03	0	-4718.52	0	-5786.82	0.00	-7154.51	0	-7868.51	0	-9778.60	0	-9976.26	0.00	-11901.02	0
Machinery	-2099.48	0.00	-2410.26	0	-3190.43	0	-4204.43	0.00	-5393.34	0	-5756.36	0	-7281.99	0	-8137.76	0.00	-9927.16	0
Electrical equipment, appliances, and components	-2040.73	0.00	-1987.05	0	-2756.39	0	-3374.73	0.00	-4015.94	0	-4605.64	0	-5611.90	0	-6080.90	0.00	-6149.34	0
Motor vehicles, bodies and trailers, and parts	98.86	0.43	1095.55	0	1190.13	0	969.53	0.00	1103.66	0	1443.46	0	993.95	0	1136.01	0.00	1604.38	0
Miscellaneous manufacturing	-5021.94	0.00	-4604.70	0	-5345.42	0	-6365.21	0.00	-7067.67	0	-7157.25	0	-7662.85	0	-7669.60	0.00	-7906.45	0
Retail trade	-8474.45	0.00	-9566.91	0	-11103.87	0	-12472.16	0.00	-13542.91	0	-14191.72	0	-15261.48	0	-15617.66	0.00	-16346.99	0
Railroad transportation	1749.90	0.00	2176.32	0	1166.81	0	-437.31	0.14	-2219.93	0	-2937.58	0	-4313.30	0	-5971.49	0.00	-6121.50	0
Pipeline transportation	6453.86	0.00	4634.50	0	3698.95	0	2663.84	0.00	7220.75	0	8477.37	0	15885.05	0	15481.13	0.00	26223.56	0
Warehousing and storage	-8817.81	0.00	-8555.07	0	-9937.50	0	-11363.80	0.00	-12591.87	0	-13008.06	0	-15148.22	0	-16602.08	0.00	-19217.33	0
Motion picture and sound recording industries	-8336.83	0.00	-8313.95	0	-7352.00	0	-6016.87	0.00	-5081.47	0	-3134.84	0	-3707.44	0	781.31	0.08	15734.22	0
Broadcasting and telecommunications	-2522.62	0.00	-1942.15	0	-2466.24	0	-2261.71	0.00	-2469.61	0	-2202.43	0	-2529.43	0	-1830.98	0.00	-2190.03	0
Waste management and remediation services	-3576.60	0.00	-4570.18	0	-6188.52	0	-6948.07	0.00	-6844.70	0	-7620.16	0	-8723.65	0	-9383.24	0.00	-12419.00	0
Educational services	-7904.79	0.00	-9517.11	0	-11494.94	0	-13060.92	0.00	-14907.80	0	-16453.14	0	-18533.10	0	-20773.58	0.00	-23569.61	0
Ambulatory health care services	-5292.11	0.00	-5717.44	0	-6944.92	0	-7544.01	0.00	-8374.80	0	-8861.36	0	-9957.88	0	-9855.35	0.00	-9166.12	0
Hospitals	-3653.74	0.00	-4339.95	0	-5818.13	0	-6798.10	0.00	-7846.97	0	-8592.06	0	-9679.74	0	-10309.16	0.00	-10814.36	0
Nursing and residential care facilities	-6106.02	0.00	-7106.23	0	-8755.19	0	-9988.44	0.00	-11226.67	0	-11756.86	0	-13043.08	0	-13469.46	0.00	-13885.18	0
Performing arts, spectator sports, museums, and related activities	-3788.72	0.00	-4274.03	0	-6101.47	0	-7437.45	0.00	-8405.02	0	-9028.49	0	-10786.96	0	-12210.50	0.00	-13520.62	0
Amusements, gambling, and recreation industries	-10046.47	0.00	-10354.35	0	-11884.74	0	-12277.30	0.00	-12923.28	0	-13874.33	0	-14995.16	0	-15146.66	0.00	-14536.56	0
Accommodation	-8629.24	0.00	-9132.53	0	-9992.66	0	-10855.51	0.00	-11949.59	0	-11809.15	0	-12189.10	0	-11948.72	0.00	-11677.92	0
Other services, except government	-8103.50	0.00	-8499.13	0	-9516.84	0	-10158.81	0.00	-10638.76	0	-11064.88	0	-11754.21	0	-11997.26	0.00	-11713.15	0

Appendix B: Robustness

Figure 7 plots the coefficients fom conditional quantile regression in the fashion explained in Section 6, including a second lag of incremental profit rates. The corresponding coefficient is significantly different from zero in only three quantiles. The signs of current and contemporary incremental profit rates as well as capital intensity and share of labor cost in total cost remain the same, but are insignificant in more cases. Demographic factors hardly change.

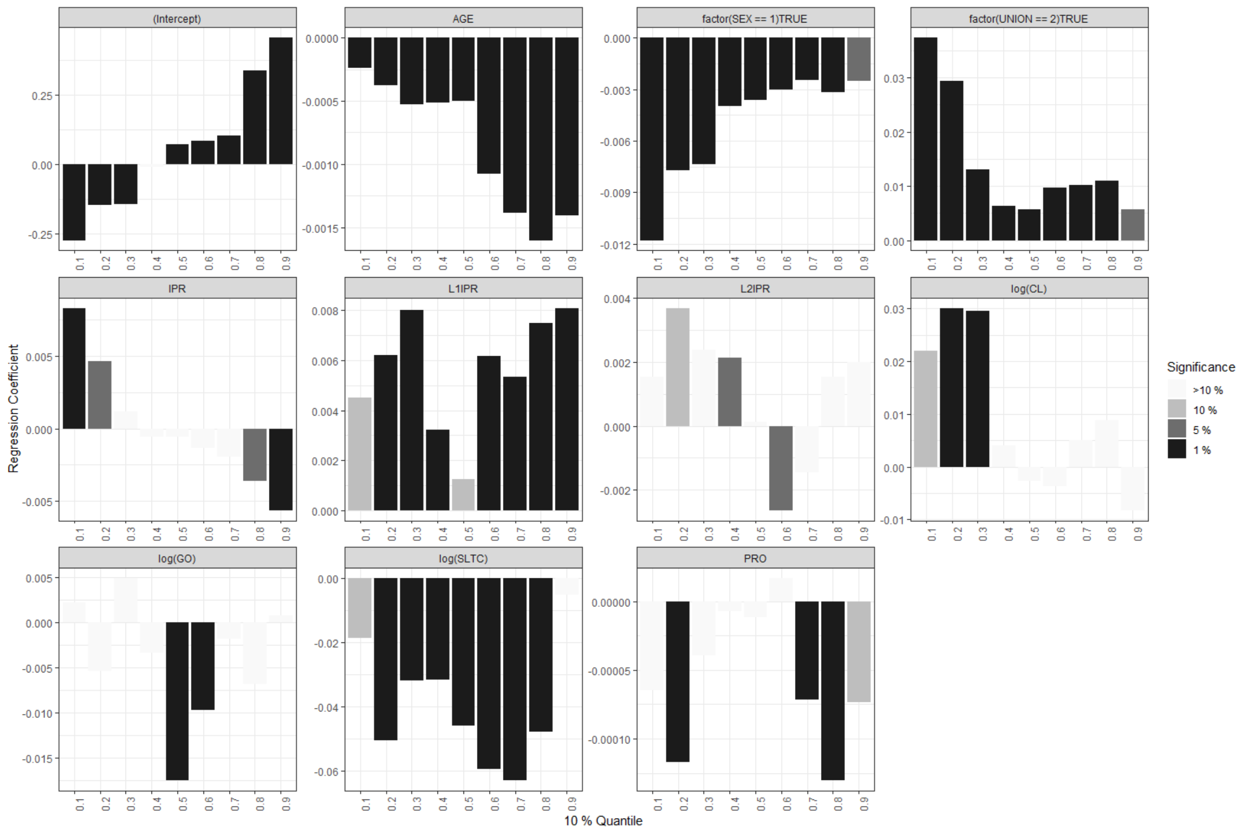

Figure 7: Conditional Quantile Regression, Impacts of Demographic and Structural Factors on year-to-year Wage Increases, Alternative Specification.

Appendix C

C.1 IPUMS CPS

On the employee level I retrieve data on wage growth, demographic information (age, sex, race), structural factors (industry, occupation and employment conditions) and union membership. I use the CPS' ASEC and restrict the sample to full-time workers who reported income from the same occupation in two consecutive years. This results in between 11 000 and 15 000 observations per year which by their weights (ASECWTH) represent 18 to 50 million workers.

After assigning NAICS07 industry codes consistent with the BEA's industry accounts to the microdata (see Section 11.3) I have between 134 and 40 000 observations per industry, representing between 21 and 691 million workers. In a year-industry crosstable there are only two empty cells, both from industry 486, pipeline transportation. Outside of pipeline and water transportation there is no year-industry combination with less than 5 observations.

I then calculate the increase in wages between the observations for years $t \in T = (1998, \ldots, 2018)$. On that basis, I calculate the yearly growth rate DINCWAGE.

$$DINCWAGE = \frac{DINCWAGE_t - DINCWAGE_{t-1}}{DINCWAGE_{t-1}} \qquad (11)$$

C.2 BEA Industry Accounts

I retrieve data on industrial value added to extract gross operating surplus and employee's compensation from BEA Industry Data Table "Components of Value Added by Industry" (1998-2018). I merge all financial and real estate categories into "5253FIRE". I also aggregate all classes of retail trade into retail trade 44RT as fixed assets and investment in fixed assets data (BEA tables 31ESI and 37ESI) are only available on this level of aggregation.

I retrieve employment data on full time equivalent employees (FTEE, BEA Table 6.5D) and, following Shaikh (2008, 187f), calculate a wage equivalent WEQ for self-employed persons SEP (i.e. partners and active proprietors that "devote a majority of their working hours to their unincorporated businesses.") I do so by calculating the sectoral share of self employed persons SEP (BEA Table 6.7 D) in employed persons EP (BEA Table 6.4 D), and multiplying it with total compensation of employees CE, which is then deducted from gross operating surplus GOS (both from BEA Table "Components of Value Added") to calculate profits PRO. Data on self-employed persons is only available on the NAICS sector level (whereas I operate on the more detailed NAICS summary level) and only going back to 1998. Note that I do not add the sum to employee compensation, as I want to retrieve the average compensation per full-time equivalent worker which is already embodied by the structure of EC and FTEE.

$$WEQ = CE \times \frac{SEP}{EP} \qquad (13)$$

$$PRO = GOS - WEQ \qquad (14)$$

While the regulating profit rate is a combination of changes in utilization, real output and real profit margins (Shaikh 2016, 299), it can be approximated by the incremental rate of return (Vaona 2011). The measure has been criticized by Dumenil and Levy (2012), but Tescari and Vaona (2014) show that the turbulent equalization results from a more sophisticated measure of the regulating profit rate hold when the IROR is used as an approximation. Following Shaikh [(2016); p300], I calculate the IROR using data on gross operating surplus GOS (BEA Table "Components of Value Added by Industry") and investment in private fixed assets IFA (BEA Table 3.7ESI).

$$r'_{i,t} \approx \frac{\Delta P_{i,t}}{I_{i,t}} \approx \frac{\Delta GOS_{i,t}}{IFA_{i,t}} \qquad (15)$$

Capital Intensity CL is calculated as fixed assets FA per full time equivalent employee FTEE (BEA Table 6.5D), with the former in Billions USD and the latter in Thousands. The share of labor cost in total cost SLTC, ie. the inverse of Botwinick (2018)'s cost-labor cost ratio gives the ratio of total employee compensation CE to toal cost TC, which in turn is approximated as the difference between total sales GO and gross operating surplus GOS. Finally, gross output GO is taken directly from the corresponding BEA Table ("Gross Output by Industry").

$$CL = \frac{FA}{FTEE} \qquad (16)$$

$$SLTC = \frac{CE}{TC} = \frac{CE}{GO - GOS} \qquad (17)$$

C.3 Crosswalks

In order to use a long sample (1998-2018), I create a crosswalk between the CPS' "IND1990" industry classification and the BEA's NAICS 3-digit codes. I use the 1990 industry classification rather than the 2002-2013 "IND" variable in the CPS as the latter is available in the ASEC supplement only from 2000 onwards.

I retrieve crosswalks between 1990 and 2000 industry classifications (IPUMS, n.d.b) and between the CPS' own industry codes IND and NAICS-resembling IND NAICS (IPUMS, n.d.a).

The former reports the percentage of observations from the 2000 classification (which has more industries) that would go in the respective 1990 categories. Following Soltas (2019, 2), I assign to every 1990 code the 2000 code with the largest percentage of observations between the two. This means that I do not perform a weighted crosswalk (in which one assigns crosswalked classifications randomly based on the given percentages) but opt for the most likely option.

I then link the CPS "IND" codes to their own "INDNAICS" classifications that resemble NAICS 2007 codes. At this point, I eliminate industries that are not present in the BEA data, namely "non-specified parts of mining", "Unemployed, with no work experience in past 5 years" and the different branches of the US military ("U.S. Army", "U.S. Air Force", "U.S. Navy", "U.S. Marines", "U.S. Coast Guard", "U.S. Armed forces, branch not specified" and "Military reserves or national guard"). The last step is unproblematic as I will eliminate industries not governed by a profit motive or in which profitability and cost structure is difficult to derive later.

Finally, I translate the CPS NAICS codes into the ones used in the BEA files.

C.4 Ignored Industries

Following Shaikh (2008) I exclude financial, insurance and real estate industries, as any estimation of their inventories, and thus fixed assets, is non-trivial. I furthermore exclude NAICS[6] industry summaries 5411 "legal services", as the data shows abnormally high profit rates, 55 "management of companies and enterprises" which reports consistently negative profits, and 3364OT "manufacturing of durable goods; other transportation equipment" which has abnormally large incremental profit rates. This is necessary as the construction of regulating profit rates depends on the deviation of incremental rates from their cross-sectional weighted annual mean, which would be distorted by abnormal rates.

In the first step of the estimation analysis, I investigate in which industries incremental profit rates and growth rates of compensation are turbulently equalizing. Those industries where turbulent equalization can be rejected are also excluded from the analysis, because I investigate the impact of turbulent competitive dynamics.

[6] Throughout this paper, whenever not specified differently, I refer to the 2012 revision of the NAICS.

Appendix D: Distribution of Growth Rates

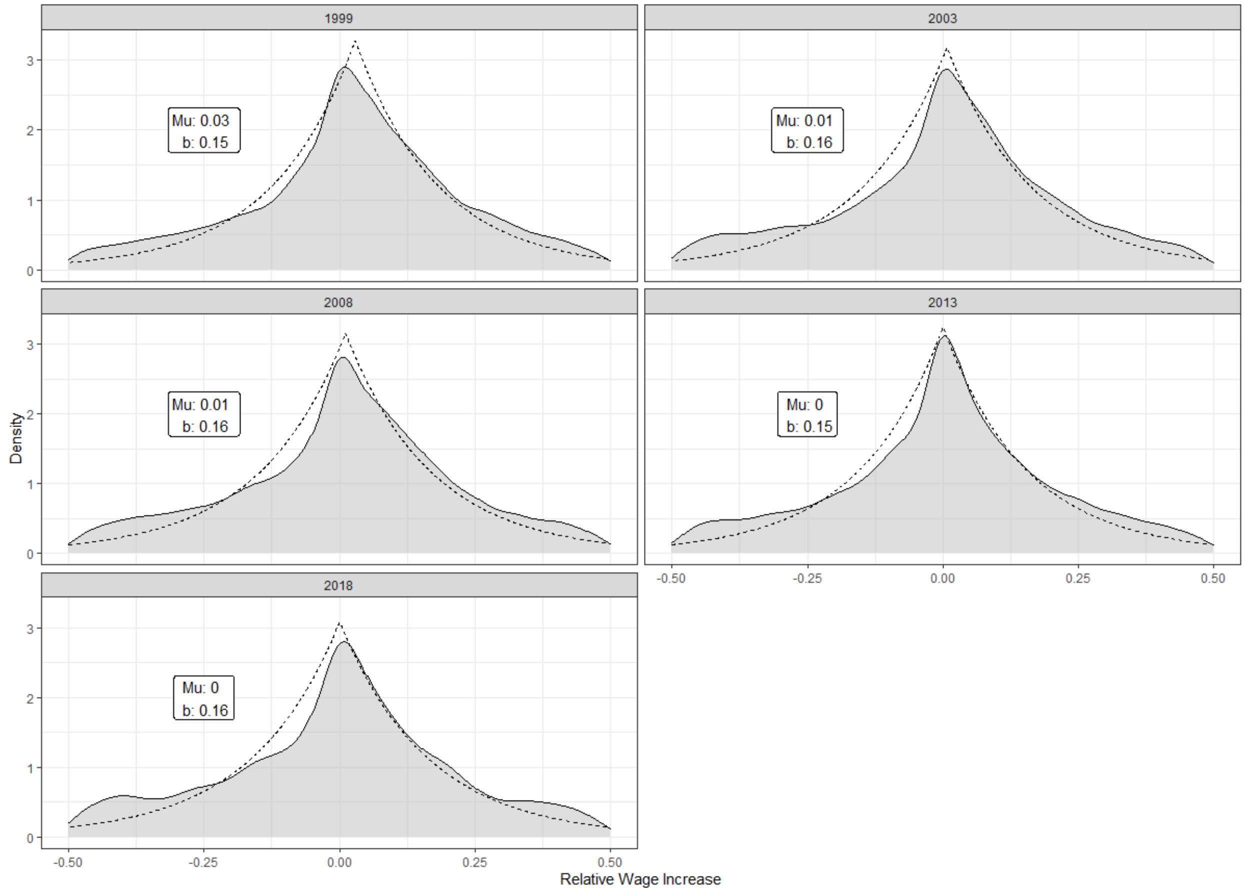

Figure 8: Laplace Distribution over Wage Growth, all observations and in 5-year-intervals. Data: CPS 1990-2018, BEA Industry Accounts 1990-2018, Own calculations and crosswalks.

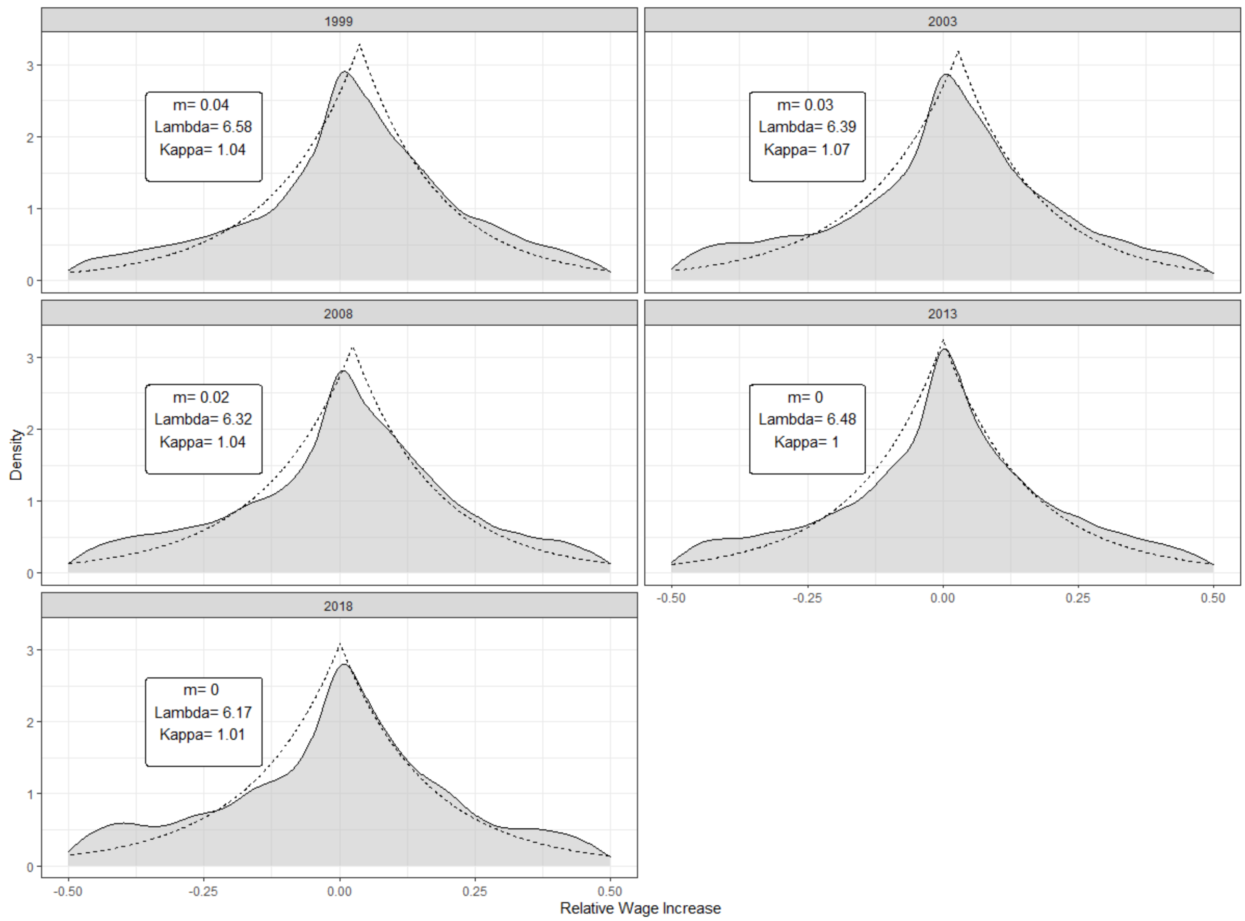

Figure 9: Asymmetric Laplace Distribution over Wage Growth, all observations and in 5-year-intervals. Data: CPS 1990-2018, BEA Industry Accounts 1990-2018, Own calculations and crosswalks.