Market Concentration and Labour Market Outcomes

Alexandre MacDonell

Major paper presented to the

Department of Economics of the University of Ottawa

In partial fulfillment of the requirement of the M.A. degree

Supervisor: Professor Gamal Atallah

ECO 6999

Ottawa, Ontario

August, 2019

Acknowledgements

I would like to thank Professor Gamal Atallah for providing his time and insights during the preparation of this research paper. I am also extremely grateful to Professor Gilles Grenier for his constructive comments and feedback for preparing this paper.

Abstract

The evaluation and legislation regarding market concentration has long been centred on consumer welfare. The impacts of decreased competition on labour market outcomes have only recently begun to receive attention. Using data from the U.S. Economic Census (ECN), years 2002, 2007, and 2012, I examine the impact of market concentration, using the Herfindahl–Hirschman Index, on three sets of outcome variables, labour bill per worker, aggregate labour bill, and share of total expenses going to labour, each with three increasingly narrow specifications of overall costs of labour, payroll costs of labour, and production workers wages. Using OLS regression, my models find a small, statistically, but not economically, significant, correlation between concentration and labour expenses at the per worker level, but large negative correlation at the aggregate level.

Table of Contents

1. Introduction

In the current era, topics of market concentration are returning to the forefront of political and economic discussions.[1] The issues are innumerable, from the effects of Silicon Valley concentration on the dissemination of information and the proliferation of “Fake News” (Khan, 2018), to the proposed merger of telecom giants AT&T and Time Warner (Krishan, 2019), to Amazon deciding to take on the food industry (MehChu, 2019), and to local news conglomerations (Minow, 2018). In the United States, the government agency responsible for enforcing competition laws is the Department of Justice (DOJ). In Canada, that duty falls to an independent federal law enforcement agency named the Competition Bureau of Canada (“the Bureau”). Among other things, the Bureau is responsible for approving or contesting mergers. These decisions are made in consideration of the Mergers Enforcement Guidelines (MEGs). Its equivalent in the United States is the Horizontal Merger Guidelines (Federal Trade Commission / Department of Justice, 2010).

The Horizontal Mergers Guidelines and MEGs both outline definitions and thresholds for anti-competitive behaviour, monopoly and monopsony effects, and other related topics.[2] Both use consumer welfare theory in their guidelines to take into account prospective efficiency gains. Yet, interestingly, and sometimes critically, the MEGs include a *codified exception* for efficiency gains.[3] This effectively means that the anti-competitive effects are weighted against the gains in

---

[1] In this paper, I will use competition and concentration interchangeably, low competition being equivalent to high market concentration.

[2] In fact, they are very closely linked, and use the same HHI definitions and classifications.

[3] Part 12: THE EFFECIENCY EXCEPTION in the 2009 publication of the Merger Enforcement Guidelines, the most recent.

efficiency that a firm receives from a proposed merger, the most prominent example being *Tervita Corp. v. Canada* (2015), wherein the Supreme Court of Canada ruled in favour of the merging parties and ruled that the proposed efficiencies, as stated by the firms, outweighed the anti-competitive effects, as argued by the Competition Bureau. In some cases, the efficiency gains come from synergies between a research and development firm and a large retailer, but in many instances, efficiencies are gained by reducing administrative redundancies.[4]

Effectively, in some cases, firms can argue that the anti-competitive effects of a merger (a negative to society) can be offset by efficiencies gained primarily by reducing their labour demand (I would argue, also a negative to society). Academic studies and Antitrust enforcement have long focused on consumer welfare theory, but activists, think tanks, and labour groups are starting to examine the broader effects on the labour market (Lynn, 2018). This paper deals only with U.S. data, but I felt it important to discuss the Canadian MEGs as it was what inspired the examination of the relationship.

This paper seeks to examine the relationship between market competition and labour expenses in the United States. I will perform a series of OLS regressions, with various specifications of labour expenses as the dependent variable, with data from the Manufacturing series of the quinquennial U.S. Economic Census (ECN) from the years 2002, 2007 and 2012, controlling for industry and year as well as value-added manufacturing. I hypothesise that there is a negative relationship between market concentration and labour expenses. In other words, I expect

[4] There are exclusions to what is considered for the purposes of the efficiency exception, namely anti-competitive behaviour like reducing output or quality, or extracting wage concessions from suppliers as a result of increased market power, but gains from layoffs are not excluded, and thus are calculated for the purposes of efficiency gains.

that as market concentration increases labour expenses will decrease. The economic theory is that, in markets with high concentration, firms will have power to exert downward pressure on wages in the labour market. However, this paper does not aim to study the mechanism of such a relationship, it merely aims to examine whether such a relationship exists. The contrary to my hypothesis would be if increased concentration led to higher labour expenses, either in the aggregate or per worker.

The results of the OLS regressions do not match my hypothesis at the per worker level. In fact, the coefficient estimates are positive, though I argue in the results section that they are not economically significant. In short, I find very little effects from concentration on labour expenses per worker. However, the results do support the notion that labour costs are indeed decreased in the aggregate. Still, there are some reasons to doubt to the substantiality of these results, which I will address near the end of Section 5.

This paper is structured as follows: Section 2 will provide a literature review, contextualizing the paper; Section 3 will be an overview of the data used, as well as an analysis of the restrictions and summary statistics; Section 4 will provide the econometric models; Section 5 will present the results; Section 6 will explore some limited robustness checks; and Section 7 will conclude. References will be in Section 8 and Tables will be at the end of the paper.

2. Literature Review

In this section, I will examine eleven papers that operate in the sphere of market competition. The primary goal is to situate this paper within the landscape of this topic. The secondary goal is to examine the expected relationship between market concentration and labour expenses.[5] First, will be several papers that examine the effects of concentration on various aspects of a firm or industry, from which one can theoretically infer relationships to wages, followed by a few papers that found differing results and used or suggested different methods to measure concentration. And lastly, I will go over three papers that directly examine the relationships I am measuring. This section is not intended to be exhaustive.

The following papers studied the effects of market concentration on factors generally presumed to impact labour wages, such as productivity, firm profit, and innovation.

Tang and Wang (2005) and Zitzewitz (2003) find a positive correlation between competition and worker productivity. Tang and Wang (2005) examine the effects of product market competition and skill shortages on the productivity of Canadian firms. The data originates from the 1999 Survey of Innovation by Statistics Canada, in which firms give their perception of the competitiveness of their industry. It also uses productivity data from the 1997 Annual Survey of Manufacturers (ASM). The paper's main findings are consistent with conventional economic thought: that firms, particularly those large and mid-sized, who perceive a high level of competition have higher productivity levels. Likewise, Zitzewitz (2003) examines competition and long-run productivity growth by comparing the U.S. and U.K. tobacco industries over the period of 1879 to 1939. The author argues that this is a useful period to analyse as access to technology was about even and the industries were monopolized at different times. The paper uses data from several sources, including the U.S. Census of Manufactures and the U.K. Census of Production.

[5] Labour expenses will take on many forms, from wages, to salary, to total labour bill, and will be marked as appropriate in each instance.

The author finds that the industries generally increased production at a faster rate during periods of competition than during the periods of monopolization.

In contrast, Acharya (2005) finds that increased concentration leads to higher total factor productivity. In his paper Acharya seeks to estimate total factor productivity (TFP) growth when accounting for non-perfect competition and non-constant returns to scale. The paper uses data from the Annual Survey of Manufacturers of 86 Canadian industries from 1990 to 2002. It has many findings regarding the structure of Canadian industries, but interestingly it finds that different measures of decreased competition are all correlated with increased TFP growth.

Some researchers touched on potentially reciprocal relationships between competition and productivity factors, such as Aghion et al. (2005) and Lee (2016). Aghion et al. sought to examine the relationship between product market competition and innovation. They posited that the relationship had an inverted U-shape, that more competition will lead to firms separating themselves technologically, and that when the firms are more neck-and-neck in technology, the greater the incentive for innovation and the larger the effect of competition. The paper uses firm level accounting data from individual UK companies, as well as administrative data used to measure technological performance, which the authors got from the U.S. patents office, spanning the period of 1968 to 1997. They use patents filed as a proxy for innovation and, because they have firm level accounting data, they use the Lerner Index, or price-cost margin, to proxy product market competition. Their results fit well with their proposed model and supported their hypotheses. Meanwhile, Lee (2016) seeks to examine the roots of “agglomeration diseconomy” by examining the manufacturing sector in South Korea. Essentially, what would cause firms not to locate themselves in a concentrated geographic area with similar firms? The paper focuses on competition in the labour market. It uses data from both the National Statistical Bureau as well as the Ministry of Employment and Labour, from 1993 to 2006. The author finds that increased competition from firms raises the wage of workers and, as such, provides disincentive to agglomeration.

Additionally, some found that the effects of concentration may not be consistent, such as Taylor (2010) and Horn et al. (1994). Taylor (2010) examines the effects that potential competition-based school reform might have on teacher's salaries. The paper uses panel data from 670 Texas schools and 335,000 teachers in 67 distinct markets. Taylor uses the Herfindahl–Hirschman Index (HHI) as a proxy for market competition between schools and finds that an increase in competition leads to higher wages for most teachers, but lower wages for teachers in concentrated markets. Meanwhile, Horn et al. (1994) sought to examine the relation between the market structure of a firm and its internal efficiency. The paper attempts to proxy internal efficiency by the structure of incentive contracts and checks whether they are optimal incentive contracts. The paper consists purely of theoretical models and therefore does not use data. It defines a model firm and uses contract theory to examine results in three markets: Bertrand, Cournot and Cartel. The authors argue that effort incentives are lowest in the Bertrand case, the most competitive, as it leads to lower prices and profits than in the less competitive Cournot and Cartel cases. They suggest that counter to common economic belief, higher competition does not automatically imply increased internal efficiency, rather that there may be a negative relation between effort incentives and the competitiveness of the product market.

While many of these papers study concentration at the industry level, some papers suggested firm level analysis was more appropriate. Kambhampati and Kattuman (2009) examined the effect of increased liberalism on market share volatility and concentration. They review Indian manufacturing data sourced from the Reserve Bank of India (RBI) compilation of firm level profit and loss accounts, and balance sheets of the large and medium firms registered in India from 1981 through 1997. They found that despite market HHI remaining relatively unchanged, individual firm market share volatility increased after domestic liberalisation in 1985 and reversed after comprehensive liberalisation in 1991. In both periods they argue, the “winners” and “losers” offset in the aggregate data, obfuscating the real structural changes. They argue that this shows the value of a shift in methodology towards firm level effects of competition rather than industry level analysis.

Some papers explicitly studied the relationship between market concentration and wages. Benmelech et al. (2018) studied U.S. Economic Census data over the period of 1977-2009 and found that local-level market concentration could explain some of the stagnation of wages over that span. Interestingly, they found that wage growth and productivity growth are more closely correlated in competitive markets. Additionally, they posit that the presence of labour unions had a tempering effect on the negative monopsonistic effects, noting that the “negative relationship between labour market concentration and wages is stronger when unionization rates are low” (Benmelech et al., p. 4). Meanwhile, Azar et al. (2019) used OLS and IV methods to examine the relationship between firm concentration and wages in the U.S., by sourcing proprietary data from an online job board. They used the HHI to calculate the concentration of the hiring market based on the shares of vacancies posted and used occupational classifications and commuting zones to classify wages and markets. They found a very strong negative correlation between concentration and real wages, stating a displacement from the 25th percentile to the 75th percentile in concentration correlated with a 17% decline in the advertised wage.

Another paper studies the decreases in labour shares. Barkai (2017) showed that the decline in labour share in the United States over the past 30 years was not offset by a corresponding increase in capital share. Using a general equilibrium model, the author found that the difference is attributed to increased markups. The author also finds that the decrease in labour share is strongly correlated with an increase in market concentration, and concludes that “the results are consistent with a model in which firms face barriers to entry, where prices are the result of monopolistic competition” (Barkai, 2017, p. 25).

On the whole, the literature is somewhat mixed on the expected relationship between market competition and worker salary. Lee (2016) states that there is a clear positive effect of increased competition on wages, Benmelech et al. (2018) posit that increased concentration can partially explain wage stagnation, Azar et al. (2019) find a strong negative correlation between concentration and wages, and Barkai (2017) links declining labour share to increased concentration. Furthermore, Tang and Wang (2005) and Zitzewitz (2003) found that increased competition raised productivity, and Aghion et al. (2005) found that it increased incentives to innovate, both of which theory says should raise wages. On the other hand, Acharya (2005) found that decreased competition was actually correlated with increased total factor productivity, and Horn et al. (1994) posited that since non-competitive firms have more profits, there is more incentive to provide effort incentive contracts. The rest of this paper will discuss the data and econometric models I used to explore the effects of market concentration on labour market outcomes, followed by a discussion of the results.

3. Data

The data used in this paper comes from multiple series of the U.S. Economic Census, years 2002, 2007 and 2012. The Economic Census is the largest and most comprehensive public source of information and statistics on businesses in the American economy. It is done every 5 years and the three sets that I chose are the most recent to be published.[6] The American Economic Census is widely used by Federal Agencies, Policymakers and Trade Groups to inform decisions and generate key economic indicators such as Gross Domestic Product (GDP) and the Producer Price Index (PPI) (United States Census Bureau, 2018).

In the U.S. literature, two primary sources were used for information on the manufacturing sector: the 5-year ECN and the Annual Survey of Manufacturers (ASM). I chose the ECN due to its slightly richer data, distinguishing between 3 classes of labour and multiple subcategories of expenditures, and most importantly that the concentration ratios were publicly calculated, as well as the market share levels of the top 4, 8, 20 and 50 largest companies.

I created the dataset by merging two series from the ECN, the Manufacturing Sector Subject Series: Concentration Ratios dataset and the Industry Series set for Detailed Statistics by Industry, for each year. This data is publicly available and replicable.[7]

The Industry data is organised around the North American Industry Classification System (NAICS), first created in 1997 by the U.S Office of Management and Budget (OMB), working in

[6] The 2017 Economic Census results will be rolled out on "a flow basis" from September 2019 through December 2021, per the official government website.
[7] On the www.census.gov/data website.

concert with its counterparts from Canada and Mexico.[8] The NAICS was established as a uniform system to better represent the economy following the adoption of the North American Free Trade Agreement.

In 2002 the ECN added questions differentiating between production workers, leased employees and all other employees. This is especially important for this paper as it allows me to isolate which group of employees are most affected by product market concentration.

The NAICS classification system is hierarchical in nature, with 2- through 6-digits representing increasingly narrow categories.[9] There are five levels in total, with the 6-digit code being the most precise classification available. If one is only using data from one country, the 5- and 6-digit codes are interchangeable.

The data that I compiled in my custom dataset is coded by the complete six-digit NAICS code and is the best data that is publicly available. The original database had the data coded by every level, 2- through 6-digits, in addition to aggregates of the top 4, 8, 20 and 50 largest companies for each NAICS code, which represents 10,885 total entries. Keeping only the unique NAICS codes for each year left 2,177 observations.[10] Since the DOJ and other antitrust enforcement organizations view product market concentration through a narrow scope, the high levels of aggregation at the 2- though 4-digit levels are not appropriate. The degree to which the lower-digit groupings can be informative is likely to vary between industries. For example, it is

[8] Statistics Canada and Mexico's Institutio Nacional de Estadistica.

[9] Per census.gov FAQ: 2-digit: the economic sector, 3-digit the subsector, 4-digit designates the industry group, 5-digit designates the NAICS industry, and 6- digit designates the national industry.

[10] These are not all unique observations as 6-digit industries will be counted again in the lower-digit parent categories.

possible that the 4-digit classification of “leather and allied products” is a suitable aggregation level and that the included firms all compete in the same markets, whereas that is less likely to be the case for the 4-digit classification for “plastic products” or “rubber products”. I believe that it is far more likely that the 6-digit NAICS classification still overestimates the number of competitors in a market than it underestimates it. Filtering to keep only 6-digit codes reduced the sample to 1,313.

Beyond that, the only restrictions placed on the sample are from the source datasets. I did not add any further limitations. In the public dataset, for reasons of privacy and anonymity, the information for some industries is supressed. The financial data for these industries is withheld to avoid disclosing data for individual companies. This can be either because there are very few firms, or because one or two firms are sufficiently large that one can infer information from the aggregate totals. The data published is subject to the customary “Threshold Rule” (Subcommittee on Disclosure-Avoidance Techniques, 1994). See Table 1 for a full accounting of the industries that were omitted in the source ECN data, along with the number of companies in the industry.

Accordingly, there are 46 unique 6-digit NAICS codes, 72 observations in total, that were omitted from this sample in at least one year (Table 1). In the final sample, there are 508 unique NAICS codes over the 3 survey years, for a final sample of 1,241 observations. The structural omissions pose some problems for this paper, as the reason for exclusion is directly tied to the relationship that is being studied. Since I am trying to examine the effects of highly concentrated industries on salary, removing the industries with the highest concentrations is problematic as it explicitly excludes some of the observations that we are most interested in. This is especially true as some of the academic research posits that the nature of market concentration is not simply linear.

It can be argued that the impact of losing a firm from a 3-firm industry is much greater than the impact of losing a firm from a 13-firm industry. This is further supported by the enforcement actions of the responsible authorities. The DOJ only intervenes in cases of high concentration. Very rarely will a merger be challenged in a deep, competitive industry.

However, there are still observations in the dataset that meet established thresholds for concern. I will use the DOJ benchmarks for concentrations, where an HHI of less than 1500 is deemed competitive, and an HHI over 2500 is deemed highly concentrated, with an HHI in between deemed moderately concentrated (Department of Justice, 2018). Under those guidelines, 42 entries in my sample, qualify as highly concentrated. Only 20 of those became highly concentrated from one survey period to the next (Table 2). However, if I loosen the requirements and count any instance of jumping one category level, there are 157 qualifying observations. Section 5.3 of the DOJ & FTC's Horizontal Merger Guidelines (2010) presumes that any HHI increase of more than 200 points in a highly concentrated market is likely to enhance market power. Eight such entries meet that criteria (Table 3). Additionally, if we simply look at any HHI increase of over 200 points, we have 237 observations.

I will primarily use the natural logarithm of the HHI as the main independent variable of interest.[11] Additionally, I will also use three different sets of dependent variables, each with three increasingly narrow specifications. The three sets of outcome variables are as follows: labour bill per worker, aggregate labour bill, and share of total expenses going to labour, as reported by the

[11] In the robustness checks section, I will also use binary variables based on the DOJ benchmarks, those instances will be clearly specified.

firms. The specifications, in increasing constriction, are overall costs of labour, payroll costs of labour, and production workers wages. The variables and specifications are defined in further detail in the following Econometric Model section.

The summary statistics can be viewed in Table 4. Mean HHI is 805.63, overall cost of labour per worker is $57,010 per year, payroll cost of labour per worker is $44,190 per year and average hourly production worker wages is $18.23 per hour. Notably, the labour share of total expenses is highly volatile, with the average total overall cost of labour share representing just over a quarter of all expenses, at 25.63%, with shares ranging from as low as 1.34% to 65.68%. By definition, the share of expenses dedication to production workers is lower, with an average of 11.73%, maxing out at 45.33%. The share of labour cost belonging to production workers varies drastically by industry, ranging from 11.62% to 87.98%, with an average of 59.29%.

4. Econometric Model

This paper will use three sets of models, each including three specifications, around the core relationship between labour outcomes and the HHI. Additionally, I will examine intra-labour changes by running a model with the production share of labour costs as the outcome variable. The method used for all models will be OLS regression.

The first set of models centres Labour Bill *per Worker* as the outcome variable.

Model 1.1:

$$lnOverallCostofLabourPerWorker_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

wherein $lnOverallCostofLabourPerWorker_{it}$ represents the natural logarithm of the overall cost of labour per worker in industry *i*, in year *t*. In the Census data, total compensation is annual payroll plus total fringe benefits; this is what I am defining overall cost of labour. The dependent variable was inputted by dividing total compensation by the average number of employees for the given industry and year.

HHI is the Herfindahl-Hirschman Index. This index is a frequently used proxy for market competition. The HHI is a measure of concentration used in antitrust law by authorities such as the DOJ and the Canadian Competition Bureau; it is also used in academic research such as in Acharya (2005), Azar et al. (2019), and Taylor (2010), among many others. In his paper Acharya demonstrated that under the assumption of homogeneous products, Cournot marketplace and Cobb-Douglas preferences, the HHI is equivalent to the Lerner Index, another commonly used proxy for competition that uses price-cost margin instead of market share. Price-cost margin information is not available in the ECN data.

The HHI is the sum of industry market shares squared. A monopoly will have an HHI of 10,000, and a perfectly competitive industry will have an HHI trending towards 0 as the number of firms goes to infinity.

$$HHI = \sum_{j=1}^{n} (v)^2$$

In which, there are n firms, with v representing the market share, in percent, of firm j.

In the Economic Census, for manufacturing only, the HHI is calculated for the top 50 largest firms by market share.

Ω_i and Ψ_t are vectors of controls for industry and year respectively. The industry vector is comprised of dummy variables along the 508 NAICS six-digit codes. The years are 2002, 2007 and 2012, with 2002 as the reference year.

$lnValueAdded_{it}$ is the observation specific logarithm of the manufacturing value added. This variable serves as a proxy for the productivity and margins of an industry. Value Added is similarly used as a control by Benmelech et al. (2018) and Acharya (2005).

Model 1.2:

$$lnPayrollCostofLabourPerWorker_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

wherein ln $lnPayrollCostofLabourPerWorker_{it}$ replaces $lnOverallCostofLabourPerWorker_{it}$ to calculate only the natural logarithm of the annual payroll per worker in industry i, in year t, not taking into account fringe benefits. It can be interpreted as a proxy for average employee salary, and may be referred to as such. The rest of the model follows the same specification as model (1.1).

Model 1.3:

$$lnProductionWorkersWagesPerHour_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

While the two preceding outcome variables in model 1.1 and 1.2 were scaled per year, $lnProductionWorkersWagesPerWorker_{it}$ is the natural logarithm of wages paid directly to production workers, specifically, scaled per hour. The average hourly wage estimate is generated from the Economic Census data by dividing total production workers wages by total production workers hours worked. The outcome variable may also be referred to as hourly production worker wages.

The outcome variables in the second set of regressions models are the *Aggregate* Labour Bills, rather than the per worker units.

Model 2.1:

$$lnTotalOverallCostofLabour_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

wherein $lnTotalOverallCostofLabour_{it}$ represents the natural logarithm of the total annual compensation in industry i, in year t, as calculated by the ECN. Total overall cost of labour and total compensation may be used interchangeably.

Model 2.2:

$$lnTotalPayrollCostofLabour_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

wherein $lnTotalPayrollCostofLabour_{it}$ replaces $lnTotalOverallCostofLabour_{it}$, once again the total annual payroll does not include fringe benefits. The rest of the model follows the same specification as model (2.1).

Model 2.3:

$$lnTotalProductionWorkersWages_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

wherein $lnTotalProductionWorkersWages_{it}$ is the natural logarithm of the total wages paid to production workers, specifically.

The third set of models examines the relationship between HHI and *Labour Share* of total expenses.

Model 3.1:

$$OverallLabourShare_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

In this model, $OverallLabourShare_{it}$ is the share of total expenses attributed to total compensation. Total compensation is the same as in model 2.1. Total expenses are the sum of total compensation, total cost of materials, total capital expenditures and the total of other expenses as stated in the census results.

Model 3.2:

$$PayrollLabourShare_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

The only change in this model is that $PayrollLabourShare_{it}$ represents the share of annual payroll, rather than total compensation, relative to total expenses.

Model 3.3:

$$ProductionWageShare_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

Keeping to form, $ProductionWageShare_{it}$ represents the share of wages dedicated to production workers, relative to total expenses.

Lastly, I will run a regression with the outcome variable being the share of labour costs attributed to production workers

Model 4.1

$$ProductionShareOfLabour_{it} = \alpha + \beta_1 lnHHI_{it} + \Omega_i + \psi_t + \beta_2 lnValueAdded_{it} + \varepsilon_{it}$$

$ProductionShareOfLabour_{it}$ is calculated by dividing total wages paid to production workers, by total annual payroll. The reason the share is based on annual payroll, and not total compensation, is to attempt to identify production workers versus non-production workers.

Dividing by total compensation would obscure some of that as production workers likely also receive fringe benefits.

5. Results

As shown in the Literature Review section, the research provides mixed results on the expected relationship between market concentration and worker wages.[12] However, the few papers that have examined explicitly the effects of concentration on wages, such as Azar et al. (2019) and Benmelech et al. (2018), found strong negative impact of increased concentration on wages.

I do not find that relationship reflected in this data, with my models, on the per worker level. In the first series of models, results shown in Table 5, a 1% increase in HHI corresponds with an increase in labour expenses at the individual level. In model 1.1, the estimated market concentration elasticity of overall cost of labour per worker is 0.031. While the elasticity is statistically significant, I argue that the result is not economically important, since a 10% increase in the concentration index leads to only a 0.31% increase in total compensation per worker. The results of a 10% increase in HHI are even smaller for annual salary per worker, at 0.15% with an elasticity of 0.015 for model 1.2, and hourly production workers wages, at 0.27% with an elasticity of 0.027 for model 1.3. However, it is important in cases like these to contextualize the numbers, as a percentage point increase of an index such as the HHI is abstract. As previously stated, the DOJ views any merger that increases the HHI by 200 basis points to be one that threatens

[12] With data differentiating between production and administrative workers, it is plausible that both positive and negative effects could be found; it could be posited that decreased competition would lower production workers wages, by reducing labour demand, and raise the wages of the administration and executives who may receive the spoils of increased profits.

competition. 200 points, taken from the mean HHI in the sample, 805.63 as shown in Table 4, is approximately 25%. Assuming the interpreted elasticity in Table 5 remains constant, a 25% increase in HHI would correspond with a 0.78% increase in overall cost per worker. That estimated increase is 0.38% for payroll costs per worker and 0.68% for production worker wages. Going from a market deemed competitive, with an HHI of 1500 at the upper bound, to a market deemed concentrated, HHI of 2500 at the lower bound, would represent a HHI increase of roughly 67%. This large increase, according to the Table 5 results, would only translate to a 2.08% increase in overall costs per worker, 1.01% for payroll costs per worker and 1.81 for production workers wages. In my estimation these numbers are not economically significant. While the papers of Azar et al. (2019) and Benmelech et al. (2018) would suggest that a sizeable increase in market concentration would correspond with a small decrease in worker wages, the data in my sample doesn't align with that. However, the estimated elasticities in Table 5 are sufficiently small that it can reasonably be stated that my model finds no wage effect at the individual level.[13]

The evidence of the impact of market concentration on aggregate labour bill, however, is significantly stronger. In the second series of models, the results of which are displayed in Table 6, an increase in HHI corresponds with a decrease in aggregate labour spending. Across the board, a 10% increase in HHI corresponds with at least a 1% decrease in aggregate labour bill across labour specifications based on the estimated elasticities. To further contextualize, as I did with the per worker models, a 200 point jump from the mean HHI, a roughly 25% increase, leads to a roughly 2.85% decrease in total overall cost of labour, with an estimated elasticity of -0.114 for

[13] That said, I believe this narrow relationship merits further research, with a more sophisticated model and richer data at the individual level – data that is not reasonably accessible to me at this stage.

model 2.1. The estimated decrease for total payroll cost is even larger at 3.23%, with an estimated elasticity of -0.129 for model 2.2. The estimated decrease for total production workers wages is smallest at 2.5%, with an estimated elasticity of -0.1 for model 2.3. A 67% increase of HHI that would accompany a change from competitive to highly concentrated, corresponds with a 7.64% decrease in total overall cost, a 8.64% decrease in total payroll, and a 6.7% decrease in total production worker wages.

These results are consistent with the concession assumed within any argument on efficiency gains; fewer expenditure inputs, including labour, are required to achieve equivalent production outputs.

Furthermore, the interpretation of the results is logically consistent between specifications. total annual payroll has the largest negative estimated coefficient, with total wages paid to production workers shrinking the least. This is intuitive due to the nature of the work being done: for example, a firm may be able to marginally shrink the production force to achieve the same output, but the ability to do so will likely be limited, as the production labour to output relationship is assumed to be fairly linear – this is less likely to be the case with support and administrative staff. I do not find it to be controversial to state that it is common upon mergers to reduce redundancies, and that those redundancies are most often created at the administrative and management levels. There is innumerable literature on the Human Resources side of Mergers dealing with prospective layoffs, such as Gutknecht and Murkison (1994) and Buono and Bowditch (1990). It is also logical that total overall cost of labour, i.e. total compensation, shrinks less than annual payroll, as pensions and benefits are less elastic than payroll in the short term. These relative elasticity factors are especially true if Unions are involved, as evidenced by

Benmelech et al. (2018). I argue that this simple model implies causality due to the economic argument of efficiency; it is logically consistent that if there are fewer firms in a market, who operate more efficiently, that gross spending on labour will be decreased in that market. The inherent worth and value of that trade-off can, and is, argued on either side, however I do not find it to be controversial to state that a relationship does exist.

To further investigate the impact of increased concentration on labour specifically, the third series of models, with the results shown in Table 7, examines the relationship between HHI and share of total expenses on labour. In this series there are 4 models, model 3.1, 3.2, 3.3, and 4.1, as defined in the Econometric Model section. To refresh, the dependant variable in model 3.1 is share of total expenses going to overall labour bill in a scale of 0 to 100; for model 3.2 it is share of total expenses going to annual payroll; for model 3.3 it is share of total expense going to production worker wages; and for model 4.1 it is share of payroll cost going to production workers wages. The results in Table 7 show that an increase in market concentration is correlated with a modest decrease in share of total expenses going to overall labour bill and annual payroll, and a slightly smaller decrease in share of total expenses going to production worker wages. It also shows a modest increase in share of overall labour bill going to production workers, though it is relatively smaller in percentage change. The models in Table 7 are linear-log regressions, therefore the -1.379 coefficient estimate for Model 3.1 can be interpreted as a 10% increase in HHI correlates to a 0.14-point decrease in share of expenses going to overall labour bill. The decrease is roughly similar for share of total expenses going to annual payroll, coefficient estimate of -1.443 in Model 3.2. The estimate in Model 3.3 is much smaller at -0.498, which can be interpreted as a 10% increase in HHI correlates with a 0.05-point decrease in share of total expenses going to production worker wages. As for Model 4.1, the coefficient estimate is 1.402, therefore a 10% increase in HHI corresponds with a 0.14-point increase to the share of total payroll costs going to production worker wages. To further contextualize, the mean share of total expenses going to aggregate labour bill is 25.63%, as shown in Table 4. Therefore a 0.14-point decrease represents roughly a 0.5% decrease. For share of expenses going to annual payroll, the mean is 20.13% thus a 0.14-point decrease represents a roughly 0.7% decrease. The mean share of total expenses going to production workers is 11.73%, therefore a 0.05-point decrease translates to a 0.4% decrease. In the case of share of annual payroll cost going to production worker wages, the mean is much higher at 59.29%. Therefore, the 0.14-point increase only represents a 0.2% change.

Interpreting those results through the same lens as the previous models: a 25% increase in HHI correlates to a 0.34-point, 0.36-point, and 0.12-point decrease for the dependant variables of Models 3.1, 3.2, and 3.3, respectively; for model 4.1, a 25% increase in HHI corresponds with a 0.35-point increase in share of annual payroll going to production worker wages. Those results relative to the means in Table 4 represent: a 1.3% decrease in share of expenses going to aggregate labour bill, a 1.8% share of expenses going to annual payroll, a 1.02% decrease in share of total expenses going to production workers, and a 0.6% increase in share of annual payroll going to production worker wages.

Repeating the interpretation with an industry going from competitive to highly concentrated: a 67% increase in HHI correlates to a 0.92-point, a 0.97-point, and a 0.33-point decrease for the dependant variables of Models 3.1, 3.2, and 3.3, respectively; for model 4.1, a 67% increase in HHI corresponds with a 0.94-point increase in share of annual payroll going to production worker wages. Again, those results relative to the means in Table 4 represent: a 3.6%

decrease in share of expenses going to aggregate labour bill, a 4.8% decrease in share of expenses going to annual payroll, a 2.8% decrease in share of total expenses going to production workers, and a 1.6% increase in share of annual payroll going to production worker wages.

While these numbers are not overwhelmingly large, I argue that they are economically significant as shares are zero-sum, so any change necessarily has an equal and opposite one. The direction of the changes is consistent with the analysis thus far, as well as the differences in magnitude; once again the category relating to annual payroll has the largest estimated effect, and production worker wages, the smallest. It is also consistent that share of annual payroll attributed to production worker wages increases, since production worker wages decrease less, relatively. The interpretation is the same: production workers are more integral to output, and therefore are relatively less expendable.

To summarize, I have found a small effect of concentration on labour expenses at the per worker level, a large negative effect on the aggregate level, and a small negative effect on the relative share of expenses level. It is interesting that the effect is much smaller as a share of expenses than on the aggregate level. It is consistent with general efficiency theory, assuming the relationship between labour and output is linear, most production functions are optimized with a set ratio of labour to capital. But more specifically, it is consistent with the findings by Barkai (2017): that the decrease in labour share is not offset by a corresponding increase in capital share.

The results can be interpreted as, to the extent that increased concentration may increase efficiency, it results in decreased expenditure on labour that is larger for non-production workers.

One difficulty with this model is that it may suffer from endogeneity. Some problems stem from the publicly available data. Due to the suppression of industries with sufficiently high concentration, the sample is certainly biased. There is also likely measurement error, but the magnitude and direction are unclear. In addition to problems that come with using the public data, there are also problems inherent to measuring competition. A major problem is defining the competition market. It is unlikely that a firm's market is necessarily or specifically national, and it is equally unlikely to be homogeneous for each industry. This problem could only be addressed on a case by case basis using administrative sales data matched with geographic shipment data, as well as by interviewing all concerned parties. This is how the DOJ and Competition Bureau determine market size, and it takes many months and resources that are neither reasonable nor achievable for a paper of this scope. It is also likely that not all firms within an industry compete in the same markets. Even if one assumes that products are homogeneous, it is plausible that the select leading firms would compete in a larger geographic market than the smaller firms.[14]

However, measurement error and sample bias are not the only sources of endogeneity. There likely is also an omitted variable bias. For example, whether a firm is a retailer or a wholesaler would affect both the market it competes in and its workers' salaries, as well as would change the relative importance of production versus non-production workers. These variables were not available in the data at the national level, and the HHI was only calculated at the national level. While the model found no wage effects on the individual level, if a firm having market power allows it to demand higher education, training or experience from its workers, then a variable for

[14] Small firms may only be able to serve locally, whereas larger firms may be able to compete nationally, for example.

minimum or average educational requirements would be useful. Those questions are not asked by the Census. As stated by Benmelech et al. (2018), unions have sizeable impacts on the effects of concentration, and I do not have a reliable way to factor that in with the data at my disposal, it is not covered in the ECN. Richer data on the employee side would allow to create a human capital model to derive expected earnings. It would be an entirely different project, and would answer a narrower question, but one could attempt to pair the HHI calculated at the national level in the quinquennial Economic Census, with the more frequent microdata in the U.S Current Population Survey. In that case, one would need to make some assumptions about the stability of HHI over the course of 5 years and accept some measurement error.

I do not believe reverse causality to be an issue. However, one may argue that higher wages might lead a firm to exit the market, thus causing increased concentration, as suggested by Lee (2016).

While I find it promising that the results match my expectations, the above issues lead me to the conclusion that it would be unwise to place too much stock in the results. The issue certainly merits revisiting with more microdata.

6. Robustness Check

The model I am estimating is quite simple and there aren't many structural assumptions made about the relationship between concentration and labour outcomes. In this section I will impose different specifications on the model to examine if it meaningfully alters the results found in the basic models. In the spirt of brevity, I will not discuss and interpret each result in depth. I will pick examples that spur some useful added analysis, The first robustness check will be to examine whether using the DOJ-defined categorizations provides a more significant estimate than continuous changes previously examined. The results found using the three categorical definitions, competitive, moderately concentrated, and highly concentrated, rather than the natural logarithm of the HHI, did not contradict previous findings. In all sets the competitive category is the reference group. The first series of models evaluating labour bills at the per worker level, resulted in negligibly small coefficients that were not statistically significant as shown in Table 8.

In Table 9, the results are shown for the series examining the aggregate labour bill. The results in this series are strong and support my previous findings. I will briefly discuss Alt Model 2.1, the dependant variable is the natural logarithm of total overall labour bill, and once again its estimate is between the larger total payroll bill and smaller total production worker wages. As this is a log-linear regression, the results can be interpreted as a 10.1% lower estimated total overall labour bill for moderately concentrated industries versus competitive ones, and 17.9% lower for highly concentrated industries. Consider that I only interpreted a 7.64% decrease in estimated total overall labour bill with a hypothetical change in HHI from 1500 to 2500. One will notice the results appear so much larger with the categorical model. Upon closer inspection, they aren't really. As shown in Table 4 and discussed in the Data Section, the mean HHI is 805.63. That is well below the threshold of concern where an industry is even categorized as moderately concentrated. For instance, 2500, the minimum threshold for highly concentrated, is an over 300% increase from the mean HHI in my sample. For comparison, a 300% increase in HHI, using the estimated HHI elasticity of total overall labour bill from Table 6, results in an estimated 34.2% decrease in total overall cost of labour bill. This shows that the magnitude of the estimated effect is sensitive to the starting size of the HHI calculated, but it is encouraging that the results are consistently strong.

In the third series, evaluating the relative shares of expenses, the results are fairly consistent with prior results (Table 10). This series is comprised of linear regression models. The expected decrease in share of total expenses going to total overall labour bill is larger than my previous findings, -1.12 for moderately concentrated and -2.85 for highly concentrated, however they are only significant at the 5% and 1% levels respectively, whereas the previous findings were statistically significant at the 0.1% level. The same explanation for why the magnitude appears larger also applies here. The only other notable differences are that the estimates for share of expenses going to production worker wages were not found to be statistically significant at all, and the share of labour expenses going to production workers is relatively larger.

As a separate series of robustness checks, I tested whether either a simple log-linear regression model, with the results in Tables 11, 12, and 13, or a quadratic log-linear model, results in Tables 14, 15, and 16, was a better model specification fit than the simple log-log regression model I had used. They were not. The signs were consistent with my findings, but the results were not uniformly statistically significant and the Bayesian Information Criterion (BIC) were much higher in the case of the quadratic function.

7. Concluding Remarks

In this paper, I sought to examine the relationship between product market concentration and labour expenditures. The literature on the topic was mixed but shaded towards a negative correlation. I used data from the U.S. Economic Census, years 2002, 2007, and 2012. I performed OLS regressions on multiple models to attempt to better determine the relationship. The results were mixed. In the per worker models I found no economically significant relationship. Whereas in the aggregate models, as well as the models of shares total expenses, I found a negative relationship. However, there are some concerns of endogeneity, sample bias, and omitted variable bias. I find this to be an interesting topic, and one that I am glad to see being broached by more researchers. I believe this paper is a productive step towards better understanding the relationship between market competition and labour expenses.

8. References

Acharya, R.C., (2005) "*Market Structure, Competition and Productivity Growth: Evidence from Canadian Manufacturing Industries.*" Industry Canada, preliminary draft.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005) "Competition and Innovation: An Inverted-U Relationship." *Quarterly Journal of Economics*, 120 (2), pp. 701-728.

Azar, J., Marinescu, I., and Steinbaum, M.I. (2019) *"Labor Market Concentration."* National Bureau of Economic Research Working Paper Series Reference No. 24147.

Barkai, S. (2017) *"Declining Labor and Capital Shares."* University of Chicago.

Benmelech, E., Bergman, N., and Kim, H. (2018) *"Strong Employers and Weak Employees: How Does Employer Concentration Affect Wages?"* National Bureau of Economic Research Working Paper Series Reference No. 24307.

Buono, A.F., and Bowditch, J.L. (1990) "Ethical Considerations In Merger and Acquisition Management: A Human Resource Perspective." *Advanced Management Journal*, 55, pp. 18-23.

Federal Trade Commission / Department of Justice (2010) "Horizontal Merger Guidelines." FTC/DOJ Washington D.C.

Gutknecht, J., and Murkison, G. (1994) "Acquisitions, Takeovers, and Mergers: An Analysis of Post-Action Effects on Attrition and Productivity." *International Journal of Commerce and Management*, 4 (3), pp. 36-49.

Horn, H., Lang, H. and Lundgren, S. (1994) "Competition, Long Run Contracts, and Internal Inefficiencies in Firms." *European Economic Review*, 38 (2), pp. 213-233.

Kambhampati, U. and Kattuman, P. (2009) "Growth Responses to Competitive Shocks: Market Structure Dynamics Under Liberalisation." *Structural Change & Economic Dynamics*, 20 (2), pp. 114-125.

Khan, L. (2018) "Sources of Tech Platform Power" *Georgetown Law Technical Review*, 2, pp. 325-334.

Krishan, N. (2019) *"The Government's Failure to Block the AT&T-Time Warner Merger Could Lead to Even Bigger Monopolies."* Mother Jones, Available at www.motherjones.com/politics/2019/03/att-time-warner-doj-donald-trump-monopolies/, Accessed 28 July, 2019.

Lee, Y-S. (2016) "Competition, Wage, and Agglomeration Diseconomy." *International Regional Science Review*, 39 (3), pp. 318-349.

Lynn, B. (2018) *"Wealth, Power, Control, and Command: Private Monopoly and the American Worker."* Open Markets, for the AFL-CIO Commission on the Future of Work and Unions.

Minow, M., (2018) "The Changing Ecosystem of News and Challenges for Freedom of the Press." *Loyola Law Review*, 64, pp. 499-556.

MehChu, N. (2019) "Whole Foods, Fresh Concerns?" *New Developments in Competition Law and Economics*. Economic Analysis of Law in European Legal Scholarship, 7, pp 123-145. Springer, Cham.

Subcommittee on Disclosure-Avoidance Techniques (1994) "Statistical Policy Working Paper No. 22: Report on Statistical Disclosure Limitation Methodology." Federal Committee on Statistical Methodology, Statistical Policy Office, Office of Information and Regulatory Affairs, U.S. Office of Management and Budget, Washington, DC.

Tang, J. and Wang, W. (2005) "Product Market Competition, Skill Shortages and Productivity: Evidence from Canadian Manufacturing Firms." *Journal of Productivity Analysis*, 23, pp. 317-339.

Taylor, L. (2010) "Competition and Teacher Pay." *Economic Inquiry*, 48 (3), pp. 603-620.

Tervita Corp v. Canada (Commissioner of Competition). (2015) Supreme Court of Canada, 3, 1 S.C.R. 161

United States Census Bureau (2018) *"About the Economic Census"* Available at the U.S. Census Bureau website: https://www.census.gov/programs-surveys/economic-census/about.html.

U.S. Department of Justice (2018) *"Herfindahl-Hirschman Index"* retrieved from the DOJ Antitrust Division Website: https://www.justice.gov/atr/herfindahl-hirschman-index.

Zitzewitz, E. (2003) "Competition and Long-run Productivity Growth in the UK and US Tobacco Industries, 1879-1939." *Journal of Industrial Economics*, 51 (1), pp. 1-33.

9. Tables

Table 1 – List of Omitted Industries

List of NAICS Code, Industry classification, and number of companies that were omitted in the Economic Census data, per survey year.

2002

NAICS Code	Industry Classification	Companies
311312	Cane sugar refining	14
311919	Other snack food manufacturing	265
311930	Flavoring syrup and concentrate manufacturing	145
312120	Breweries	347
312221	Cigarette manufacturing	13
316212	House slipper manufacturing	12
325221	Cellulosic organic fiber manufacturing	8
325992	Photographic film, paper, plate, and chemical manufacturing	379
326192	Resilient floor covering manufacturing	50
331311	Alumina refining	7
331312	Primary aluminum production	27
331411	Primary smelting and refining of copper	11
333313	Office machinery manufacturing	95
333611	Turbine and turbine generator set units manufacturing	93
335224	Household laundry equipment manufacturing	13
336112	Light truck and utility vehicle manufacturing	69
336411	Aircraft manufacturing	184
336414	Guided missile and space vehicle manufacturing	12
336992	Military armored vehicle, tank, and tank component manufacturing	31
339995	Burial casket manufacturing	148

2007

NAICS Code	Industry Classification	Companies
311213	Malt manufacturing	17
311311	Sugarcane mills	16
311312	Cane sugar refining	14
311313	Beet sugar manufacturing	12
311919	Other snack food manufacturing	286
311930	Flavoring syrup and concentrate manufacturing	150
312112	Bottled water manufacturing	250
312120	Breweries	373
312210	Tobacco stemming and redrying	13
312221	Cigarette manufacturing	20
314992	Tire cord and tire fabric mills	14
315192	Underwear and nightwear knitting mills	21
315221	Men's and boys' cut and sew underwear and nightwear manufacturing	7
315993	Men's and boys' neckwear manufacturing	45
316211	Rubber and plastics footwear manufacturing	46

316992	Women's handbag and purse manufacturing	113
322122	Newsprint mills	16
325182	Carbon black manufacturing	13
325221	Cellulosic organic fiber manufacturing	15
325312	Phosphatic fertilizer manufacturing	50
327111	Vitreous china plumbing fixture and china and earthenware bathroom accessories manufacturing	24
327211	Flat glass manufacturing	19
331112	Electrometallurgical ferroalloy product manufacturing	20
331311	Alumina refining	12
334111	Electronic computer manufacturing	413
335222	Household refrigerator and home freezer manufacturing	19
335224	Household laundry equipment manufacturing	14
335912	Primary battery manufacturing	43
336411	Aircraft manufacturing	221
336414	Guided missile and space vehicle manufacturing	14
336415	Guided missile and space vehicle propulsion unit and propulsion unit parts manufacturing	17
336991	Motorcycle, bicycle, and parts manufacturing	462
337129	Wood television, radio, and sewing machine cabinet manufacturing	264

2012

NAICS Code	Industry Classification	Companies
311213	Malt manufacturing	19
311313	Beet sugar manufacturing	14
322122	Newsprint mills	15
327213	Glass container manufacturing	19
335221	Household cooking appliance manufacturing	85
335222	Household refrigerator and home freezer manufacturing	15
335224	Household laundry equipment manufacturing	3
335228	Other major household appliance manufacturing	20
336414	Guided missile and space vehicle manufacturing	16
336415	Guided missile and space vehicle propulsion unit and propulsion unit parts manufacturing	16

Table 2 – List of Industries that increased to become Highly Concentrated

list of NAICS Code, Industry classification, and year in which they became classified as Highly concentrated the per the DOJ criteria (HHI > 2,500).

NAICS Code	Industry Classification	Year
311223	Other oilseed processing	2007
311919	Other snack food manufacturing	2012
311930	Flavoring syrup and concentrate manufacturing	2012
312120	Breweries	2012
312229	Other tobacco product manufacturing	2007
312230	Tobacco manufacturing	2012
315234	Women's and girls' cut and sew suit, coat, tailored jacket, and skirt manufacturing	2007
316214	Women's footwear (except athletic) manufacturing	2007
316993	Personal leather good (except women's handbag and purse) manufacturing	2007
322214	Fiber can, tube, drum, and similar products manufacturing	2007
325312	Phosphatic fertilizer manufacturing	2012
325613	Surface active agent manufacturing	2012
332992	Small arms ammunition manufacturing	2012
334112	Computer storage device manufacturing	2007
334613	Magnetic and optical recording media manufacturing	2007
335110	Electric lamp bulb and part manufacturing	2012
336112	Light truck and utility vehicle manufacturing	2007
336411	Aircraft manufacturing	2012
336991	Motorcycle, bicycle, and parts manufacturing	2012
337125	Household furniture (except wood and metal) manufacturing	2012

Table 3 – List of Industries that significantly increased to become Highly Concentrated

list of NAICS Code, Industry classification, and year in which they became classified as Highly concentrated the per the DOJ (HHI > 2,500)criteria and increased by at least 200 points in HHI.

NAICS Code	Industry Classification	Year
311422	Specialty canning	2012
315192	Underwear and nightwear knitting mills	2007
316211	Rubber and plastics footwear manufacturing	2007
325110	Petrochemical manufacturing	2012
334111	Electronic computer manufacturing	2007
334112	Computer storage device manufacturing	2012
335912	Primary battery manufacturing	2007
336415	Guided missile and space vehicle propulsion unit and propulsion unit parts manufacturing	2007

Table 4 – Summary Statistics

Variable	Mean	Standard Deviation	Min.	Max.
Herfindahl-Hirschman Index for 50 largest companies	805.63	700.14	2.6	4,671.70
Overall Cost of Labour per Worker ($/year)	57,010	18,260	17,680	155,520
Payroll Cost of Labour per Worker ($/year)	44,190	13,300	15,280	113,250
Hourly Production Worker Wages ($/hour)	18.23	5.17	7.9	51.74
Total Overall Cost of Labour ($1,000)	1,776,917	2,402,799	9,105	20,200,000
Total Payroll Cost of Labour ($1,000)	1,379,165	1,859,138	7,228	15,900,000
Total Production Worker Wages ($1,000)	794,440	1,082,474	3,086	9,680,220
Value Added ($1,000)	4,996,388	8,854,077	24,401	116,000,000
Total Expenses ($1,000)	9,404,172	28,500,000	30,377	728,000,000
Labour Share 1 (%)	25.63	10.17	1.34	65.68
Labour Share 2 (%)	20.13	8.35	0.96	56.71
Labour Share 3 (%)	11.73	5.43	0.54	45.33
Production Share of Annual Payroll (%)	59.29	12.78	11.62	87.98
Observations				1241

Notes:

Data sourced from U.S. Economic Census (2002, 2007, 2012)
Labour Share 1 - share of Total Expenses attributed to Total Overall Cost of Labour
Labour Share 2 - share of Total Expenses attributed to Total Payroll Cost of Labour
Labour Share 3 - share of Total Expenses attributed to Total Production Worker Wages

Table 5 – Regression Output results for Natural Logarithm of Labour Bill per Worker

	Model 1.1	Model 1.2	Model 1.3
	b/se	b/se	b/se
lnHHI	0.031***	0.015*	0.027***
	(0.007)	(0.006)	(0.007)
lnValueAdded	0.030***	0.032***	0.025***
	(0.007)	(0.006)	(0.007)
2007	0.181***	0.145***	0.120***
	(0.004)	(0.004)	(0.004)
2012	0.306***	0.275***	0.248***
	(0.005)	(0.004)	(0.005)
Observations	1241	1241	1241
R-sqr	0.979	0.981	0.973
BIC	-381.7	-648.3	-394

Notes:
models as specified in Econometric Models section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 6 – Regression Output Results for Natural Logarithm of Aggregate Labour Bill

	Model 2.1	Model 2.2	Model 2.3
	b/se	b/se	b/se
lnHHI	-0.114***	-0.129***	-0.100***
	(0.015)	(0.015)	(0.015)
lnvalueadded	0.697***	0.699***	0.724***
	(0.015)	(0.015)	(0.015)
Year=2007	-0.038***	-0.074***	-0.093***
	(0.009)	(0.009)	(0.009)
Year=2012	-0.035**	-0.065***	-0.105***
	(0.011)	(0.010)	(0.011)
Observations	1241	1241	1241
R-sqr	0.992	0.993	0.992
BIC	1510.5	1453.4	1506.1

Notes:
models as specified in Econometric Models section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 7 – Regression Output Results for Share of Total Expenses Going to Labour

	Model 3.1	Model 3.2	Model 3.3	Model 4.1
	b/se	b/se	b/se	b/se
lnHHI	-1.379***	-1.443***	-0.498**	1.402***
	(0.347)	(0.286)	(0.190)	(0.416)
lnValueAdded	0	0	0	0
	0.000	0.000	0.000	0.000
2007	-3.703***	-3.774***	-2.435***	-0.788**
	(0.201)	(0.166)	(0.110)	(0.241)
2012	-4.468***	-4.108***	-2.932***	-1.917***
	(0.236)	(0.195)	(0.129)	(0.283)
Observations	1241	1241	1241	1241
R-sqr	0.954	0.954	0.952	0.958
BIC	9239.7	8759.6	7748	9691.8

Notes:
models as specified in Econometric Models section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 8 – Robustness Check, series 1 – Regression Output Results for Labour Bill per Worker

	Alt Model 1.1	Alt Model 1.2	Alt Model 1.3
	b/se	b/se	b/se
Moderately Concentrated	0.002	-0.007	0.004
	(0.011)	(0.010)	(0.011)
Highly Concentrated	0.021	0.013	0.041*
	(0.019)	(0.017)	(0.019)
lnValueAdded	0.029***	0.032***	0.023***
	(0.007)	(0.006)	(0.007)
2007	0.183***	0.146***	0.122***
	(0.004)	(0.004)	(0.004)
2012	0.308***	0.277***	0.250***
	(0.005)	(0.004)	(0.005)
Observations	1241	1241	1241
R-sqr	0.979	0.981	0.972
BIC	-345.6	-634.7	-370.9

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 9 – Robustness Check, series 1 – Regression Output Results for Aggregate Labour Bill

	Alt Model 2.1	Alt Model 2.2	Alt Model 2.3
	b/se	b/se	b/se
Moderately Concentrated	-0.101***	-0.111***	-0.058*
	(0.024)	(0.024)	(0.024)
Highly Concentrated	-0.179***	-0.187***	-0.120**
	(0.042)	(0.041)	(0.042)
lnValueAdded	0.704***	0.707***	0.729***
	(0.015)	(0.015)	(0.015)
2007	-0.043***	-0.080***	-0.098***
	(0.009)	(0.009)	(0.009)
2012	-0.045***	-0.077***	-0.114***
	(0.011)	(0.011)	(0.011)
Observations	1241	1241	1241
R-sqr	0.992	0.992	0.992
BIC	1565.6	1531.1	1567.8

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 10 – Robustness Check, series 1 – Regression Output Results for Share of Total Expenses Going to Labour

	Alt Model 3.1	Alt Model 3.2	Alt Model 3.3	Alt Model 4.1
	b/se	b/se	b/se	b/se
Moderately Concentrated	-1.116*	-1.077*	0.092	2.389***
	(0.531)	(0.439)	(0.291)	(0.633)
Highly Concentrated	-2.847**	-2.606***	-0.319	2.265*
	(0.920)	(0.762)	(0.505)	(1.098)
lnValueAdded	0	0	0	0
	0.000	0.000	0.000	0.000
2007	-3.760***	-3.837***	-2.476***	-0.773**
	(0.201)	(0.167)	(0.110)	(0.240)
2012	-4.584***	-4.230***	-2.975***	-1.793***
	(0.235)	(0.195)	(0.129)	(0.280)
Observations	1241	1241	1241	1241
R-sqr	0.954	0.953	0.951	0.958
BIC	9256.2	8788.1	7765.7	9693.5

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 11 – Robustness Check, series 2 – Regression Output Results for Labour Bill per Worker

	Model 1.1	Model 1.2	Model 1.3
	b/se	b/se	b/se
HHI200	0.006**	0.002	0.006***
	(0.002)	(0.002)	(0.002)
Value added ($1,000)	0.000**	0.000***	0.000*
	0.000	0.000	0.000
2007	0.184***	0.147***	0.122***
	(0.004)	(0.004)	(0.004)
2012	0.310***	0.279***	0.251***
	(0.005)	(0.004)	(0.005)
Observations	1241	1241	1241
R-sqr	0.979	0.981	0.972
BIC	-361.1	-632.6	-385.3

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 12 – Robustness Check, series 2 – Regression Output Results for Aggregate Labour Bill

	Model 2.1	Model 2.2	Model 2.3
	b/se	b/se	b/se
HHI200	-0.013	-0.016*	-0.006
	(0.007)	(0.007)	(0.007)
Value added ($1,000)	0.000***	0.000***	0.000***
	0.000	0.000	0.000
2007	0.025	-0.012	-0.029
	(0.017)	(0.017)	(0.017)
2012	0.052**	0.022	-0.014
	(0.020)	(0.020)	(0.020)
Observations	1241	1241	1241
R-sqr	0.973	0.973	0.971
BIC	3093.1	3083.1	3166.7

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 13 – Robustness Check, series 2 – Regression Output Results for Share of Total Expenses Going to Labour

	Model 3.1	Model 3.2	Model 3.3	Model 4.1
	b/se	b/se	b/se	b/se
HHI200	-0.357***	-0.356***	-0.056	0.447***
	(0.082)	(0.068)	(0.045)	(0.098)
ValueAdded	0	0	0	0
	0.000	0.000	0.000	0.000
2007	-3.691***	-3.767***	-2.455***	-0.828***
	(0.201)	(0.166)	(0.111)	(0.240)
2012	-4.496***	-4.142***	-2.961***	-1.910***
	(0.235)	(0.194)	(0.129)	(0.280)
Observations	1241	1241	1241	1241
R-sqr	0.954	0.954	0.951	0.959
BIC	9234.8	8756.5	7757.3	9676.1

Notes:
models as specified in Econometric Models section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 14 – Robustness Check, series 3 – Regression Output Results Labour Bill per Worker

	Model 1.1	Model 1.2	Model 1.3
	b/se	b/se	b/se
HHI200	0.019***	0.011**	0.016***
	(0.004)	(0.004)	(0.004)
HHI200-squared	-0.001***	-0.001**	-0.001**
	0.000	0.000	0.000
lnValueAdded	0.030***	0.033***	0.024***
	(0.007)	(0.006)	(0.007)
2007	0.181***	0.145***	0.120***
	(0.004)	(0.004)	(0.004)
2012	0.307***	0.276***	0.249***
	(0.005)	(0.004)	(0.005)
Observations	1241	1241	1241
R-sqr	0.98	0.981	0.973
BIC	-381.4	-647.3	-393.8

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%,   *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 15 – Robustness Check, series 3 – Regression Output Results for Aggregate Labour Bill

	Model 2.1	Model 2.2	Model 2.3
	b/se	b/se	b/se
HHI200	-0.042***	-0.049***	-0.031***
	(0.009)	(0.009)	(0.009)
HHI200-squared	0.001	0.001*	0.001
	0.000	0.000	0.000
lnValueAdded	0.706***	0.710***	0.731***
	(0.015)	(0.015)	(0.015)
2007	-0.037***	-0.073***	-0.093***
	(0.009)	(0.009)	(0.009)
2012	-0.038***	-0.069***	-0.109***
	(0.011)	(0.010)	(0.011)
Observations	1241	1241	1241
R-sqr	0.993	0.993	0.992
BIC	1500.2	1438.5	1521.1

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion

Table 16 – Robustness Check, series 3 – Regression Output Results for Share of Total Expenses Going to Labour

	Model 3.1	Model 3.2	Model 3.3	Model 4.1
	b/se	b/se	b/se	b/se
HHI200	-0.471*	-0.544***	-0.098	1.110***
	(0.194)	(0.161)	(0.109)	(0.234)
HHI200sq	0.01	0.014	0.004	-0.043**
	(0.011)	(0.009)	(0.006)	(0.013)
lnvalueadded	-1.981***	-1.455***	-0.532**	1.073**
	(0.329)	(0.273)	(0.185)	(0.399)
Year=2007	-3.409***	-3.541***	-2.361***	-0.995***
	(0.198)	(0.164)	(0.111)	(0.240)
Year=2012	-4.119***	-3.847***	-2.839***	-2.107***
	(0.233)	(0.193)	(0.131)	(0.282)
Observations	1241	1241	1241	1241
R-sqr	0.957	0.956	0.952	0.96
BIC	9180.5	8715.4	7753.2	9654.9

Notes:
models as specified in Robustness Check section;
b - Coeffecient Estimate;
se - Standard Error;
* Significant at 5% , ** Significant at 1%, *** Significant at 0.1%;
All models controled for NAICS six-digit-Industry effects, results supressed for visual clarity.
BIC - Bayesian Information Criterion