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Same Same, but Different?

Exploring the Effect of Unemployment on the Frequency of Strikes versus Lockouts in Norway between 1909 and 1938

Mads Randen

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Supervisors:
Kalle Moene
Anders Kjelsrud

Abstract

This thesis uses newly digitized data on industrial conflict to explore the relationship between the frequency of industrial conflict and unemployment. The data covers Norwegian industrial conflicts and ranges from 1909 to 1938. Unlike the majority of previous research, this analysis separates between strikes and lockouts. What is the relationship between unemployment and industrial conflict in the period? Do employers and unions respond differently to unemployment? These are the question this thesis aims to answer.

The thesis explores earlier theoretical and empirical work and discusses arguments for separating the two forms of industrial conflict. The empirical analysis in this thesis indicates that separation is needed as the relationships look to be different for the two forms of industrial conflict. The validity and potential explanations of the different estimates are also discussed.

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Preface

With this thesis, I conclude my Master in Economics, and hopefully my long (some will say too long) stay at the University of Oslo. I am thankful for the people I have met, and the things I have learned. The biggest thanks are however reserved for the Norwegian welfare state. Thank you for letting me spend six years of my life together with my best friend and archenemy, Blindern.

I am very grateful for the advice, discussions, and support I got from my supervisors Kalle Moene and Anders Kjelsrud. In times when I was uncertain about where this project was headed, your feedback proved to be indispensable. There is a long way from the study hall at Blindern to the "battle of Menstad", but you made the 100-year-old data come to life. In addition, thank you for letting me be a part of the project as a research assistant and letting me use the data. It has been very rewarding. Any mistakes still present in this thesis are my responsibility.

Thank you to all my fellow students on the 11th floor. Individual work is less lonely done together. A special thanks to Alfred Løvgren and Lars Tennbakk Bockman for reading my thesis. In addition to badly needed breaks, you provided much-needed feedback.

Lastly, thank you, Else. For everything. My partner.

May 2023, Oslo,
Mads Randen

1 Introduction

Strikes and lockouts have made and still make a substantial impact on society. They affect firm output, individual economic outcomes, and how wealth is divided in society. However, in a world created by economists, consisting of rational actors with perfect information, industrial conflicts would not exist. The profit and utility-maximizing parties would simply find a Pareto-optimal solution. All the same, industrial conflicts do happen. The task for economists is to understand why.

This thesis explores the relationship between industrial conflict and unemployment. I answer the following two questions: What is the relationship between the frequency of industrial conflict and unemployment? Does it differ for strikes and lockouts? These are the main research questions of the thesis. To answer these questions I try to estimate the relationship between unemployment and industrial conflict in Norway between 1909 and 1938. The thesis differentiates between different forms of industrial conflict, strikes and lockouts, and explores whether the relationship differs between the two. I use standard economic theory about employment, wages, and bargaining power to form hypotheses about the relationship.

I explore theories related to asymmetric information, the business cycle, and a model incorporating the union leadership to explain why industrial conflicts happen (Moene, 2015; Rees, 1952; and Ashenfelter and Johnson, 1969). Higher unemployment can affect the outside options of the workers, the wage demands from the unions, and the cost of a conflict for the firm. Most theoretical work predicts a negative relationship between unemployment and the frequency of strikes. This is also confirmed by previous empirical results discussed in section 2.5. The relationship between the frequency of lockouts and unemployment is more unclear. However, I use the theoretical work to show the frequency of lockouts may be affected by different forces compared to strikes. These hypotheses are tested using new data.

The data I am using stems from newly digitized reports that the Norwegian Confederation of Trade Unions (LO) published each year.[1] The data contains information about each industrial conflict in the period 1909-1938. Among other things, the data lets me separate

[1]All the statistical work in this thesis is done in R. See chapter 3 for a more detailed description.

between different forms of industrial conflict. The data have, as far as I understand, not been analyzed empirically in this setting before. The results will thus themselves be a contribution to the literature. I also use different measures of unemployment in the period. For this, I rely, among others, on the work done by Grytten (1994).

I find that the frequency of strikes and lockouts responds differently to different levels of unemployment in the period. The relationship between the frequency of strikes and unemployment is estimated to be negative, while the opposite, but less precisely estimated, is true for lockouts. This also holds for several different specifications of the equations estimated, but not for all. In addition, it holds when using different measures of unemployment in the period. The negative relationship between strikes and unemployment is in line with theory and previous empirical research discussed in this thesis. The economic forces driving the frequency of lockouts are far less explored, but I show that they may be different from the ones driving strikes.

The estimates in this thesis do not, however, have a strict causal interpretation. The effect is not possible to isolate as the data material is quite limited. The results are nevertheless interesting and underline the need for separating strikes and lockouts in further research.

Previous research has in large part not separated between different forms of industrial conflict. Many acknowledged and widely used studies of strikes are in reality studies of conflict in general (Hamark, 2022, p.1893). This is the case for a number of reasons.

First, many economists do not think that strikes and lockouts differ, at least not when analyzing conflict. Hicks (1963), for instance, used the term strike to describe any kind of industrial conflict, no matter who "began it" as he puts it. He proceeds to call the distinction "useless" for his analysis. I am of a more nuanced perception.

Second, the data material has been quite limited. Despite the recommendation from the International Labor Office (ILO), several national statistical agencies have not distinguished between different forms of industrial conflict (Van der Velden, 2006, p.342). This has made research hard as it is impossible to explore a feature of the data that is not present. My data gives me the ability to make this distinction. Besides, lockouts occur quite frequently during this period. This is an ideal basis for exploring whether the two types of conflicts actually respond differently to the same economic forces.

Understanding the mechanisms behind industrial conflict is, in addition to being academically interesting, important for several reasons. First, conflict is costly. Large conflicts can cripple the output of the affected sectors. Second, the bargaining power and the relative strength between workers and capital owners are important for understanding how the output is divided between them. Understanding the mechanisms behind conflicts, therefore, has consequences for our understanding of distribution. Third, the period I am exploring was important for the development of the Norwegian welfare state. Understanding the mechanisms behind industrial conflicts are important in understanding this crucial historical period. If the frequency of strikes and lockouts is affected differently by the same economic forces, this has implications for how the phenomenon should be investigated in the future.

To make a meaningful analysis of the relationship between conflicts and unemployment, it is important to make some delimits to the thesis. It is important to underline that my goal is not to perfectly explain why industrial conflict occurs, nor to develop a new theoretical framework. Because, whatever the reason, industrial conflicts happen. My main contribution is the empirical findings. A broader explanation of industrial conflict is left to others. In addition, I limit myself to only focus on the frequency of industrial conflict. Other interesting questions regarding the length, size, or similar features of the industrial conflict are left unanswered, for now.

The remainder of the thesis is structured as follows. Firstly, I present some existing theories about industrial conflict and the bargaining process in chapter 2. I then link this theory to unemployment and form some hypotheses about the potential relationship between conflict and unemployment. I show how unemployment can affect the frequencies of strikes and lockouts differently. Since most of the existing literature is focused on strikes, the control variables in the regressions are mainly based on theory from the strike literature. Chapter 3 gives an overview of how the data were collected, and the potential weaknesses of this method. The quality of the data is also discussed in this chapter. In addition, some summary statistics are presented. Chapter 4 discusses the method, while the results are presented in chapter 5. These results are discussed in chapter 6 before some concluding remarks are made in chapter 7.

2 Theory and Previous Empirical Work

Both strikes and lockouts consist of a suspension of work. The International Labour Organisation (ILO) defines a strike as "a temporary work stoppage carried out by one or more groups of workers with a view to enforcing or resisting demands or expressing grievances, or supporting other workers in their demands or grievances" (International Labour Organization, 1993). Lockouts are accordingly characterized as "a total or partial temporary closure of one or more places of employment, or the hindering of the normal work activities of employees, by one or more employers (...)" (Ibid). The keen eye will discover that the definitions are very similar. The crucial difference between a strike and a lockout is, however, that the former is initiated by workers, and the latter by the employer. This could have some implications for the analysis of the bargaining process, which is something I will discuss in this chapter. First, however, I examine how economists analyze industrial conflict in general.

2.1 The Hicks-paradox

Industrial conflict is hard to explain, at least for economists. The outcome will never be Pareto optimal since the pie the parties are sharing becomes smaller as a result of the conflict (Kennan, 1986, p.1091). This is called the Hicks-paradox and is a useful starting point when discussing industrial conflict.

In the influential book *Theory of Wages*, Hicks (1963) argued that a conflict, in general, is a sign of failure by the union (p.146). The union members will seldom be better off with a strike. This is because a strike is costly for the firm, and the employer is going to be willing to use some capital to avoid a conflict. If a strike is initiated, the employer is only prepared to pay for the loss he or she suffers from the remainder of the strike. This amount is shrinking as the strike goes on (Ibid, p.145). Thus, if both parties have all the information necessary, a solution will almost always be possible.[1] Hicks did not find it valuable to separate between strikes and lockouts when he analyzed the problem.

[1] Hicks argued that some conflicts are impossible to avoid. He believed that the unions had to strike at least occasionally to keep the threat trustworthy. The result would not be better for the union in the short term but kept the employers aware of the union's power (Hicks, 1963, p.146).

Similar to many other economic problems, most models assume that the unions are maximizing some sort of objective function. This could be the discounted value of its members' income, but many other maximands have been suggested (Moene et al., 1993, p.93). The firm would like to maximize its present discounted value. In its simplest form of the problem, the union would like to maximize the wage, and the firm would like to keep it as low as possible. As just seen, with perfect information and rational actors, the solution to this problem does not involve a conflict.

2.2 Asymmetric Information

Different approaches have been put forward to meet the Hicks-paradox. A common way is to include some sort of asymmetric information. If the management has more information about the profits of the firms, a strike can be rational for the workers. The unions can gain information about the state of the firm with a strike. Let's take a look at a simple model from Moene (2015). The model analyzes both when the firm and when the union has private information. A model with asymmetric information is also discussed by Hayes (1984), among others.

I start by examining when the firm possesses private information about its state. For instance, the firm may know about a positive demand shock for its product. The firm maximizes its profit and minimizes cost. It consequently has an incentive to be overly pessimistic about its state in order to lower wage expectations among the workers (Moene, 2015, p.19).

The union understands this and will take the information from the firm with a pinch of salt. The union believes that the state of the firm is good with a probability of $(1 - s_w)$ and bad with a probability of s_w. The firm's actual added value in the period is given by R when the conditions are good, and θR, with $\theta < 1$, when the conditions are bad.

The union can either decide to pursue an aggressive or acquiescent strategy. With the aggressive strategy, the union demands a wage, w, and threatens with a strike that lasts a share of the contract period, $\alpha < 1$. The profit for the firm is given by:

$$\pi = \begin{cases} R - w & \text{When the firm yield} \\ (1-\alpha)(R-q) & \text{When the firm do not yield} \end{cases} \tag{2.1}$$

In this setting, q is the negotiated wage after a strike. The union will demand the highest possible wage that is still in the self-interest of the firm. This must meet the constraint $R - w \geq (1-\alpha)(R-q)$. Solving for w gives: $w = \alpha(R-q) + q$. The demand from the union is the negotiated wage plus the total savings of the firm by not having a work stoppage. An important point is that no strikes would happen if the firm actually was in a good state. The firm will be better off accepting the wage claim from the union. If, on the other hand, the firm actually was in a bad state, a strike would occur. The expected wage for the workers pursuing an aggressive strategy can be expressed by:

$$\begin{aligned} E(w) &= (1 - s_w)(\alpha R + (1 - \alpha)q) + s_w((1 - \alpha)q) \\ &= (1 - s_w)\alpha R + (1 - \alpha)q \end{aligned} \tag{2.2}$$

On the other hand, the union can choose a less aggressive strategy and demand a wage that the firm always will accept. Using the same logic as before this will be: $\tilde{w} = \alpha\theta R + (1-\alpha)q$.

The union maximizes its expected payoff when choosing its strategy. The expected wage from the aggressive strategy must be bigger than the certain wage from the acquiescent strategy. In other words, $E(w) > \tilde{w}$. Simplifying the expression gives us the inequality:[2]

$$(1 - s_w) > \theta \tag{2.3}$$

The union will choose the aggressive strategy if it believes, with a high probability, the state of the firm is good relative to the shrinkage factor θ. It is important to note that a strike will never happen if the union chooses an acquiescent strategy. The strike will only take place if the union pursues an aggressive strategy, and the firm actually is in a bad condition.

I now take a look at the situation when the union has private information. The union could have information about their ability to withstand a work stoppage, and Moene (2015) uses the strike fund as an example.[3] As before, the union will never tell the firm how big their strike fund actually is.

When the firm actually believes that the union is able to withstand a lockout, it offers a wage, w, that it knows the union will accept. The offer is pared with a threat of a lockout that lasts a fraction of the contract period, β. The workers' payoff is

[2] The calculations are included in the appendix.

[3] One could also argue that the inner morals in the union could be another example. The union leadership could have information about the motivation for a conflict among its members. The union would however never tell the firm if the motivation for a work stoppage was low.

$$u = \begin{cases} w & \text{When union yield} \\ (1-\beta)q & \text{When union do not yield} \end{cases} \tag{2.4}$$

Since the firm believes the union is ready for a lockout, it will offer $w = (1-\beta)q$. The profit for the firm is $\pi^* = R - (1-\beta)q$. The union will always accept the offer, and a lockout will not take place.

Nevertheless, the firm can do better if the union is not ready for a work stoppage. It can force the workers to accept a lower wage by offering a wage that makes workers indifferent between having a job and not, q_0. The union will not accept this wage if it has sufficient funds for a lockout. Because the firm does not have information about the state of the union its expected profit can be written:

$$\begin{aligned} E(\pi) &= s_l(1-\beta)(R-q) + (1-s_l)(R-q_0) \\ &= (1-s_l\beta)R - (s_l(1-\beta)q + (1-s_l)q_0) \end{aligned} \tag{2.5}$$

This aggressive strategy is only favorable if $E(\pi) > \pi^*$. This is the case when

$$(1-s_l)((1-\beta)q - q_0) > s_l\beta R \tag{2.6}$$

It is important to note that a lockout will only happen when the firm chooses an aggressive strategy, and the union is ready for a work stoppage.

The left side of the inequality is falling in q_0. This is the lowest wage the union will accept if it has no strike fund. This means that a higher q_0 is related to fewer lockouts. This is because the potential for a lower wage, and therefore a higher profit for the firm, is smaller when the alternative wage is higher.

The left side of the inequality is growing in q. In the scenario of an aggressive strategy, q is only paid if there are sufficient strike funds. It is paid with certainty in the case of an acquiescent strategy. This makes the aggressive strategy more attractive.

The simple model outlined in this section shows that asymmetric information can help explain how industrial conflict can happen. It is simplified and may not capture all elements, but provides important insight into how the causes of strikes and lockouts may differ from each other. The determinants for the different types of conflicts are not the same in this model. I connect this model with unemployment in section 2.4.

2.3 A Model with Three Parties

Another solution to the Hicks-paradox was introduced by Ashenfelter and Johnson (1969). It introduces the union file and ranks as an actor in the bargaining process, in addition to the union leadership and management. In this setting, the problem, therefore, involves three parties. The goal of the union leaders is 1) ensuring survival of the union, and 2) securing the political faith of the leaders (p.36). For the most part, these goals are achieved by meeting the expectations of the union members.

Nonetheless, when the wage expectations of the members are much larger than management is willing to accept, the union leaders are in a more difficult situation. The union leaders must choose: 1) signing an agreement with a lower wage increase than expected from the members, or 2) initiating a strike (p.37). The first alternative risks getting declined by the members, the union leadership risk losing support and the union risks losing members. This is not in line with the goals of the union leadership. The second alternative, even if it is not in the members' "best interest", could lead to a higher utility for the union leaders. The smallest wage increase that the union members accept is a diminishing function of the length of a strike, $y_A = v(S)$.[4]

The idea is that in the case of a strike, the members will moderate their wage demands as a function of the length of the strike. This relationship is illustrated in figure 2.1. After the strike has lasted for a while, the union leaders can agree to a wage level that the members are satisfied with. Ashenfelter and Johnson (1969) uses this reasoning to find the optimal strategy for the parties. The firm maximizes its present discounted value and has to choose whether a conflict is in its interest. The details of the math are outlined in the appendix.

The inequality that must be met is

$$y_0 > \frac{\alpha P - \beta \tilde{W}(1 - (\tau/r)y_*)}{\beta \tilde{W}(1 + \tau/r)} \tag{2.7}$$

Where y_0 is the initial wage demand, α is the production size, P is the product prize, β is the number of workers, $\tilde{W}$ is the wage in the previous contract period, y_* is the lowest

[4]Ashenfelter and Johnson (1969) represents the function as:

$$y_A = y_* + (y_0 - y_*)e^{rS}$$

The lowest acceptable wage increase goes to a minimum wage y_*. This is the level that the union would not accept even if the strike goes to infinity.

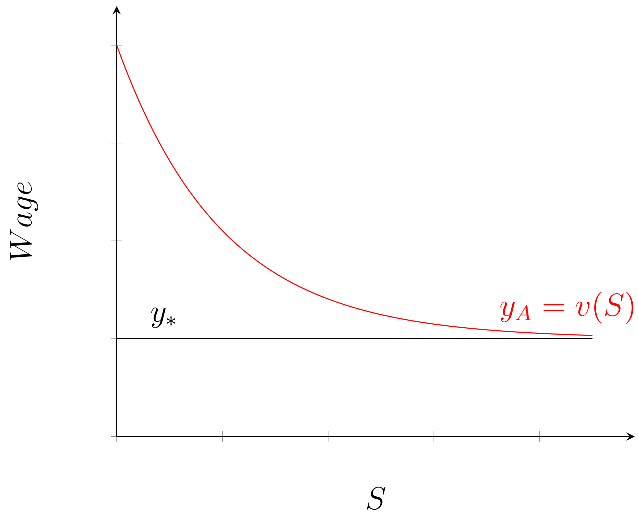


Figure 2.1: Length of Strike and Wage Demand

The wage demand is a falling function of the time of the strike. It approaches y_* which is the lowest acceptable wage for the union.

acceptable wage no matter how long the strike is, and r and τ are the discount rates.

The probability of a strike is rising with a higher initial wage claim, y_0, and it is falling with the minimum acceptable wage, y_*. It is also less likely, the greater P, α/β, and r, y_*.

This model has another way of resolving the Hicks-paradox. The model with three parties can also help predict and make a meaningful hypothesis about the relationship between industrial conflict and unemployment. It is important to note that this model does not distinguish between strikes and lockouts.

2.4 Conflict, Unemployment and Bargaining Power

The relationship between wages and unemployment is widely discussed. Standard economic theory states that higher unemployment reduces the relative bargaining power of the workers. As the father of the famous Phillips-curve put it: one should expect that wages increase when demand for labor is high, unemployment is low and business owners overbid each other in order to get workers (Phillips, 1958, p.283). A similar framework may also be transferable to industrial conflict.

When exploring this theory, it may be fruitful to distinguish between different forms of conflict. A strike is a tool to secure the workers higher wages and more benefits in times of improved business conditions. Low unemployment also comes with a series of strategic advantages for the workers. Firms have a smaller pool of potential workers to replace them, workers are more willing to strike if they have an option elsewhere, and owners are more reluctant to lose out on the growing market share (Rees, 1952). This theory would therefore lead to a negative relationship between unemployment and strikes.

The same logic can be used about lockouts. Business owners have a higher chance of success if unemployment is high. The capital owner also has less to lose if the demand for their product is lower.[5] This would lead to a higher frequency of lockouts when unemployment is high. The relationship is in other words positive, and opposite from the one with strikes.

The arguments outlined above are intuitive, but the relationship between unemployment and industrial conflict may not be that straightforward. In a comment to Rees, O'Brien (1965) points out some weaknesses. While it is true that workers have more to gain with a strike in good periods, employers have more to lose. The employers should therefore be willing to go further to meet the demands from the unions in good times (O'Brien, 1965, p.654). Thus, Rees' arguments may not be satisfactory. To find better explanations, I use the models described in the previous sections. They may be used to form more robust hypotheses.

Strikes: I start by looking at the theory for strikes. In the simple model with asymmetric information the inequality $(1 - s_w) > \theta$ had to be satisfied for the union to choose an aggressive strategy. A fair assumption is that the probability of a good state is related to the unemployment rate. Since the unemployment rate is closely related to the business cycle, one could represent the probability as a function of the unemployment rate. In other words

$$s_w = f(U), \text{ Where: } \frac{\delta f(U)}{\delta U} > 0 \tag{2.8}$$

Accordingly, $(1 - s_w)$ is declining in U. In times with low unemployment, the probability of a good state is higher. Using this logic, the union will choose an aggressive strategy more often when unemployment is low. Remember that a strike only will happen when the union chooses an aggressive strategy. A hypothesis is therefore that lower unemployment leads to more strikes.[6]

Ashenfelter and Johnson (1969) argues that unemployment is related to the initial claim from the union y_0, see equation 2.7. A lower unemployment rate should increase the wage

[5] It is fair to assume that the business cycle and unemployment level are highly correlated.

[6] On the other hand, an alternative interpretation is that the probability of a firm actually being in a bad state could be bigger when unemployment is high. This could point in the other direction. It is important to be aware that different effects are in play. I have underlined what I believe is the most important effects.

demand, and therefore increase the probability of a strike. The reasoning is the same as before, workers have an easier time finding a higher-paying job elsewhere and it will be less opposition against a strike among the members since it is easier to find part-time work during the conflict (p.40).

Lockout: A lockout only happens when an aggressive strategy is used according to the model from Moene (2015). For that to happen the inequality $(1-s_l)((1-\beta)q-q_0) > s_l\beta R$ must be satisfied, as shown in 2.6. The connection to unemployment may be more double-edged than with the case of strikes, and more effects are in play.

First, as discussed in the previous section, low unemployment is expected to be related to the probability of a sufficient strike fund. More workers without a job lead to larger expenses and smaller incomes for unions. I, therefore, expect that lower unemployment leads to a higher s_l, less aggressive employers, and less lockout.

Second, lower unemployment could lead to a higher alternative wage. This means that the lowest wage the workers are willing to settle with, q_0, is higher. A higher q_0 makes an aggressive strategy less attractive for the employer. This effect also points towards fewer lockouts.

Third, the q could also be affected. This comprises wage after a conflict is expected to be higher when unemployment is low. The union needs a higher wage to not go into conflict.

To summarize:

$$\begin{aligned} &\text{Low unemployment} \rightarrow \text{higher } s_l \rightarrow \text{less lockouts} \\ &\text{Low unemployment} \rightarrow \text{higher } q_0 \rightarrow \text{less lockouts} \\ &\text{Low unemployment} \rightarrow \text{higher } q \rightarrow \text{more lockouts} \end{aligned} \tag{2.9}$$

One can distinguish between strikes and lockouts on whether it is the union or the employer who has committed themselves to a certain position and a certain demand. Commitment means to bind oneself to the mast, making it costly to back down or concede. The most "aggressive" side may be able to commit itself and obtain an edge in the negotiations. If the union is the first to bind itself, we are in danger of a strike. If the employer is the first to bind itself, we are in danger of a lockout.

When a union binds itself, it can use the strike threat as a test for whether the firm faces profitable market conditions or not. Unions are then able to discriminate between profitable and not-so-profitable firms. When an employer, on the other hand, binds himself, he can use the threat of a lockout as a test of whether the union has strike funds or not or have other unions' sympathies or not.

This section attempts to connect the theory about industrial conflict to unemployment. It is important to note that this is a small sample of the existing theory, and it is possible to interpret the theory in different ways. The important takeaway is that unemployment can play a role in the bargaining process between unions and employers. In addition, the effect could be different when analyzing from the unions' or the employers' perspective.

2.5 Previous Empirical Work

Several researchers have tried to explain the mechanisms behind industrial conflict using empirical data. I summarize some of their findings in this section with special attention to the results related to unemployment and industrial conflict.

Some of the earlier studies of unemployment and industrial conflict came from Rees (1952). He studied US data between 1915 and 1949 and analyzed the frequency of strikes in relation to the business cycles. The data shows a procyclical pattern, meaning that the average number of strikes happened as the economy expanded and was falling again in the contraction period. Rees argues that business cycles and employment are highly correlated and that this may explain the pattern. His arguments are discussed in the previous chapter.

Ashenfelter and Johnson (1969) also test the model outlined in section 2.3. They used American quarterly data ranging from 1952 to 1967. The dependent variable is the number of strikes that are started in a given quarter. The model includes real wage changes, company profits, seasonal effects, and unemployment. All the estimates for unemployment are negative and significant. One weakness of these estimates is that data on the number of expiring contracts was not available for Ashenfelter and Johnson on a quarterly basis. They, therefore, had to assume that this number is constant. I am at least in some specifications of the estimation able to control for the number of expiring contracts.[7]

Hibbs (1987, Chapter 1) explores, among other things, the relationship between unemployment and industrial conflict. He uses data from 10 advanced economies in the period 1950-1969. In addition to unemployment, Hibbs Jr. controls for development

[7]Farber (1978) argued that the model from Ashenfelter and Johnson should be tested using microdata. The data includes 10 companies and 80 contracts that are negotiated between 1954 and 1970. In addition to the general unemployment rate, he controls for the rate of return, labor share of total sales, and previous real wage changes among other things. The results, however, suffered from a small data set (Kennan, 1986, p.1121). Only 21 strikes were a part of the sample.

in wages, company profits, bargaining systems, and political variables in different specifications of the model. The effect of unemployment is negative and significant in every specification. The chapter concludes that the inverse relationship between strikes and unemployment shows that workers are able "to capitalize on the strategic advantages of a tight labor market" (Ibid, p.49). It is important to note that Hibbs Jr. does not estimate the relationship between unemployment and lockouts. It is unclear whether the data he is using has a clear distinction between different forms of industrial conflict. The dependent variable in his analysis is a measure of strike volume. It includes the frequency, duration, and size of the conflict.[8]

Paldam and Pedersen (1982) study annual data on 17 countries in the period 1948 to 1975. The relationship between unemployment and the frequency of industrial conflict is mixed across countries. The dependent variable in this study includes both strikes and lockouts (p. 510). Pencavel (1970) uses British quarterly data and finds a significant negative relationship between industrial conflict and unemployment.

To summarize, most empirical studies surveyed do find a negative relationship between industrial conflict and unemployment. Most of the studies include variables on changes in wages, and some also include controls for political variables in addition to unemployment. An important insight is that none of these influential and well-cited studies estimate the equations without lockouts as the dependent variable. Some of them mention that industrial conflict includes both strikes and lockouts, and some do not mention lockouts at all. There may be many reasons for this. Hamark (2022) gives an overview of previous research on the separation of industrial conflicts and why this rarely is done. Among other things, he underlines that the data material is limited. Many researchers have used data from ILO that do not separate between different forms of conflict (p.1894). In addition to this, possible explanations could be that the theories that are tested often do not separate between different forms of conflict or that lockouts happen so seldom that the interest is limited.

Be that as it may, there is some research on the subject. For instance, Van der Velden (2006) compares the correlation of unemployment and frequency of strikes and lockouts in the Netherlands from 1890 to 1940. The overall result is that strikes are weakly negatively correlated with unemployment, and lockouts are weakly positively correlated with unemployment (p. 357). A simple correlation must of course always be interpreted with caution, but this result can point towards that lockouts are counter-cyclical while

[8]The measurement is calculated by: $Strike\,volume = frequency \times duration \times size = \frac{strikes}{1000\,workers} \times \frac{worker-days\,lost}{striker} \times \frac{strikers}{strike}$

strikes are pro-cyclical. One additional interesting result is that the variations explained by the correlation are very different. For instance, in the 1920s 23 percent of the variation in strike frequency is explained by unemployment, but only 0.5 percent of the variation in lockouts are explained in the same period (Van der Velden, 2006, p.357-358). Van der Velden argues that this in itself is an argument to separate the conflicts.

The theory and empirical results discussed in this section allow me to form some hypotheses about the relationship between unemployment and industrial conflict. For strikes, it seems reasonable to expect a negative relationship. Both the theory and the previous empirical work point in this direction. However, it is important to be aware that the picture is not clear, and opposing effects are in play. As for lockouts, making a hypothesis is harder. Previous research is limited and the reviewed theory is not conclusive. The empirical results are also quite limited. Nevertheless, both theory and empirical studies suggest that it is reasonable to explore whether the effect is different between the two forms of industrial conflict.

3 Data and Summary Statistics

The data I use is collected from the Norwegian Confederation of Trade Unions (LO, 1909-1938) and was digitized as part of a research project called "HAMAK". I worked as a research assistant on the project and participated in the digitization. The analysis in this thesis is based on historical data that can suffer from several shortcomings. Thus, I devote some extra space to explain how the data are collected.

LO published annual reports containing information about strikes, lockouts, and other conflicts. See figure A1.8 in the appendix for an example of how the raw data is structured. Each observation in the table represents one conflict. This is typically a conflict in one firm, but there are also examples of other observations. For instance, a whole profession in a city. The total amount of data that has been digitized as part of this project is quite big: in total 30 reports, each with more than 100 observations on average.

In order to minimize the workload and the manual process, we utilized a method called optical character recognition (OCR). This is a broad collective term for techniques that are used for transforming information typically stored as a picture into a text file (Mori et al., 1992, p.1030). In our case, OCR was used to transform PDF files of the tables into readable text files that could be used in statistical software in a meaningful way.[1] Despite the advantages of the OCR-engine, much of the data had to either be checked manually or digitized manually all together.

3.1 Data of Industrial Conflict

The newly digitized data range from 1909 until 1938.[2] It contains information on every conflict that was recorded among the member organizations of LO each year. The data

[1]All the analysis, and data processing were done in R. This includes converting files, picture manipulation, and use of OCR. For OCR we used the Tesseract-engine that was developed by HP and later Google (Smith, 2007, p.629). Important R-packages used in this process were "*pdftools*" (for handling PDF), "*magick*" (image manipulation), and "*tesseract*" (The OCR-engine) (Ooms, 2021, 2022a, 2022b)

[2]The oldest report digitized is from 1909, but it also includes some conflicts that started in 1908. This is because conflicts that were not finished in the previous year were included in the next year's report too. When estimating the models, and descriptive statistics, these observations are not included. This is because they do not include the full number of conflicts that started in 1908.

Strike	2,658
Lockout	689
Blockade	20
Other	2
NA	74
Total	3,443

Table 3.1: Frequency of Industrial Conflicts

The table shows the frequency of different forms of industrial conflict in the data. Strikes are the most usual conflict. However, lockouts make up a non-negligible part of the data. Conflicts that are not one of these categories are minimal. All tables in this thesis are created using the Stargazer or Texreg packages (Hlavac, 2018; Leifeld, 2013).

has information about the size, the length, and the outcome of the conflicts in addition to several other variables. It also contains information about the location, union affiliation, and the start and end date of the conflicts are part of the data. These variables are important in the merging process that is described in section 3.3.

I categorized the conflicts with string detection. This means that a strike is categorized as a strike if the character string "str" is part of the description of the conflict. For lockouts "loc" was the string that was used. This way of categorizing the observations accounted for nearly all of the observations. Still, it is important to be aware that some observations are counted twice. This is because they are labeled as "Strike/Lockout" or something similar. The phenomenon is quite rare. The total number of observations in the original data set is 3411 compared to the sum from table 3.1 of 3443.

The data has several shortcomings. First, it was collected a long time ago, and the methods for collecting data were different from today. One can imagine that data collection and systematization were not as consistent as if it was done today. Second, the effort to digitize the data was partly automated by an R-script, and partly done manually. Typing errors or errors related to automation can happen. Third, the data only contains conflicts involving unions that are a part of LO. This may have implications for what statistical population we are considering and is important to be aware of. However, for my analysis, I think it is reasonable to assume that the data covers most industrial conflicts in Norway during the period. Gjerløw and Rasmussen (2022) use data from the same source for a partly overlapping time period. They argue that the unions had to apply to the confederation before they initiated a strike. The strike funds were centralized and approval was needed to get compensated for the costs. Thus, the unions had a big incentive to report the conflict to the confederation (p.610-611).[3]

3.2 Data of Unemployment

I use five different measures of unemployment. One from Statistisk Sentralbyrå (SSB) (1948), one from Grytten (1994), one linear transformation based on the SSB-data, one that is available at a union level, and one that is available on a geographical level. The different measures of unemployment make me able to utilize different dimensions of the conflict data set. This section introduces the measures and briefly discusses each measure's shortcomings and advantages.

SSB: Statistics Norway (SSB) collected unemployment data for the relevant period (Statistisk Sentralbyrå (SSB), 1948). The data is reported on a monthly level. This allows me to merge the unemployment and conflict data on a finer level compared to data that is only available on a yearly level. The data is reported in percentages as most people are used to when it comes to unemployment. However, an important question in this setting is: in percentages of what?

The conventional way of measuring the unemployment rate is the percentage of the workforce that is reported unemployed. In Norway, this is now done by surveys (Sandvik, 2020). At the start of the 20th century, the measure of unemployment was created using data from the unions. The official data from SSB is therefore "unemployment among union members as a percentage of union membership" (Statistisk Sentralbyrå (SSB), 1948, p.363). In order to use this as an unbiased estimate of the unemployment rate in Norway, I have to assume that the union members are a representative sample of the Norwegian population. This may be a bold assumption.

Grytten (1994) wrote his PhD about unemployment in the interwar period (1918-1940) and discusses different unemployment measures. His arguments are discussed more in-depth in appendix A1.3. Grytten also estimated what he believes is a more representative unemployment rate. This is, however, only available on a yearly level and is used when suitable.

The linear transformation: The relationship between the unemployment measure from SSB and Grytten seems to be linear. For that reason, I also estimated some of the models

[3] Gjerløw and Rasmussen (2022) also checks the quality of their data by comparing it to reports from Statistics Norway. They find no big flaws.

with a linear transformation of the SSB-data. Since the transformation is monotonic, the sign and significance level of the estimates does not change. The point estimate is, on the other hand, affected. A more detailed discussion of transformation can be found in appendix A1.3.

The union level: Another measure of unemployment stems from the same source as the SSB-data. I have digitized data from LO (1909-1938). The data is available every year at a union level. It is important to underline that unemployment is reported as the number of workdays lost due to unemployment. This number is divided by the number of members in the union that year and finally divided by the number of days in a year. The final product can therefore be interpreted as the average percentage of the year a union member is unemployed. This measure of unemployment suffers from the same drawbacks as the SSB-data. Still, it has the advantage that it is available on a union level. This makes me able to perform empirical work which otherwise would not be possible.

The geographical level: In the interwar period (1918-1939), some public job placement offices existed. They reported the number of incidents of people looking for a job annually.[4] However, these offices only existed in around 50 cities and smaller towns. The total population in these cities only accounted for about 28-29 percent of the total population in Norway. In addition to that, the offices did not divide clearly between people searching for a job and people that were unemployed. This means that the distinction between partially unemployed people and fully unemployed people is unclear (Grytten, 1994, p.15). Besides, the numbers are high relative to the population of the cities. In some instances, the reported number is higher than the population in the city. This is because individuals could be counted several times a year.

Another drawback of this measure is that it is reported in absolute figures, and accordingly not adjusted for population/workforce changes. One could assume that the population in the cities was constant in the period. This is however not reasonable. The Norwegian population grew significantly between 1919 and 1938 (Statistisk Sentralbyrå (SSB), 2023). For that reason, I have tried to correct for this by dividing the measure of unemployment by the population in each city. The result is a measure that could be interpreted as the number of inquiries to the public job placement offices per citizen. This transformation, however, is based on some restrictive assumptions. SSB published yearly reports which, between 1920 and 1930, include the population of Norway's biggest cities (Statistisk Sentralbyrå (SSB), 1919-1938). However, they did not report these figures after 1930. I have assumed that the share of the Norwegian population living in each city stays

[4]The reports were digitized from the appendix of Grytten (1994).

constant between 1931 to 1938.[5] This may be a bold assumption that does not take changing moving patterns and other demographic concerns into account. I, therefore, use both the transformed and untransformed versions of this unemployment measure when estimating my models. The reader should keep these assumptions in mind when interpreting the results.

Despite these drawbacks, the reports do have some benefits. They capture the geographical dimension. It is possible to connect this measure of unemployment with the geographical dimension of the conflict data. It also captures the actual amount of people that were searching for jobs, both organized and unorganized workers.

3.3 Completing the Data Sets

I use in total four different data sets. One using monthly data, one with yearly data, one with yearly data on a union level, and one using yearly data with geographical information. Some concerns related to the creation of these data sets must be addressed. The most critical problem is that conflicts are lost when merging, leading to less variation in the data.

This is not a big problem with the data sets on a monthly and yearly level. The only observations that are lost are the conflicts missing a start date. This is in total 90 out of 3411 observations. It is reasonable to assume that these observations are randomly distributed across the time period. However, this does mean that I slightly underestimate the average frequency of monthly/yearly conflicts.

A more serious concern relates to the data on a union level and a geographical level. The data set on a geographical level consists of 845 strikes and 195 lockouts. When compared to table 3.1, one can see that a substantial amount of conflicts are lost creating this data set. The main reason for this is that only observations from cities with a population of over 10 000 people in 1920 are used.[6] This is done in order to get a balanced panel. In addition, including even smaller cities could lead to introducing more noise in the models without getting much more information. Conflicts are also lost because I only have unemployment data on a geographical level from 1919 onward, and 461 observations do not have information about where the conflict happened at all.

For the union data set, 1656 strikes and 442 lockouts remain in the data. The reason for this is that just a sample of the unions is a part of the merging process. To merge,

[5] I use data from Statistisk Sentralbyrå (SSB) (2023) for the yearly population, and the rate of the population living in each city is from 1930.

[6] Det Statistiske Centralbyrå (1922) include the list of the biggest cities in Norway in 1920.

I need observations both for unemployment and the number of strikes in the union that year. Since some unions dissolve and new ones are created during the period, this process is vulnerable to mistakes. For instance, if there is no recorded conflict for a union one specific year, does that mean that there were no conflicts or does it mean that the union did not operate that year? 51 unique unions are a part of the data set in total.[7] I use only 17 of these unions in order to reduce the chance of mistakes. The unions that are chosen are mainly the ones with a complete time series. In addition, some of the largest unions are also a part of the merger.[8] This data set is therefore an unbalanced panel which is important to be aware of.

This section underlines that the different data sets used in this thesis are not always comparable. First, they use different measures of unemployment that are not comparable. Second, the data set on a union and geographical level include fewer conflicts. We are therefore considering different statistical populations, and the resulting estimates can not be directly compared across the data sets.

3.4 Other Determinants of Industrial Conflict

Several variables affect the frequency of conflict. This section includes a discussion about some variables earlier research, both theoretical and empirical, has considered important. The variables are desirable to include in my models as far as possible. Because the original data are old, some variables may not be available on a level that is possible to use or they are not available at all. The source and specification of the data that is merged with the existing data set are therefore also included in this section.

Wages: It is reasonable to believe that previous changes in real wages could affect industrial conflict. One could argue that if real wages previously have been increasing, the initial claim from the unions will be lower (Ashenfelter and Johnson, 1969, p.41).[9] Another way of looking at it is that when the real wages have been rising slowly or even falling, the unions will be more militant (Farber, 1978, p.267). The data on wages in this

[7] These are the unique unions after attempts to adjust for changing names, mergers etc.

[8] The unions that are a part of the data are: Norsk Baker- og Konditorforbund, Norsk Bokbinder- og Kartonasjearbeiderforbund, Norsk Centralforening for boktrykkere, Norsk Formerforbund, Norsk Jern- og Metallarbeiderforbund, Norsk Treindustriarbeiderforbund, Norsk Skinn- og Lærarbeiderforbund, Norsk Skotøyarbeiderforbund, Norsk Stenindustriarbeiderforbund, Træarbeiderforbundet, Norsk Arbeidsmandsforbund, Norsk Høvleriarbeiderforbund, Norsk Papirindustriarbeiderforbund, Norsk Kjøttindustriarbeiderforbund, Norsk Kjemisk Industriarbeiderforbund, Norsk Kommuneforbund, Norsk Bekledningsarbeiderforbund.

[9] This is the y_0 from the model by Ashenfelter and Johnson (1969). A lower initial claim is associated with fewer strikes in their model

period is limited. I have used yearly data from Statistisk Sentralbyrå (SSB) (1948). This is the hourly wage of industry workers and is used as a proxy for the changes in wages in the period. Since I am interested in the percentage wage change in the year prior to the bargaining process, wages are given by ΔW_{t-1}. I subtract the percentage change in inflation to make it the real wage change. The variable that is used in my analysis is therefore given by: $\Delta Realwage = \Delta Wage - \Delta Inflation$. The inflation data also stems from Statistisk Sentralbyrå (SSB) (2017). In addition to real wage changes, I also control for whether the nominal wage change last year was decreasing. The reason is that nominal wage change may be more salient for the workers.

Political variables: The political climate could affect my estimates as well. Researchers have argued that unions are less willing to strike if labor and socialist parties are in serious contention for power (Hibbs, 1987, p.41). Ross (1960) argues that strikes are damaging for the Labor parties since it repels middle-class voters that the party needs. In addition, the worker's dissatisfaction can be channeled into the political sphere. These effects are stronger when the Labor Party are in power (p.235). The Labor Party grew rapidly to be Norway's biggest party in the period and held office for the first time in 1928. Although their first period in power was short-lived, the left side of Norwegian politics increased their political power significantly in the period.[10] I control for when The Labor Party was in office with a dummy variable.

Institutions: The change in institutions and the framework for bargaining could be important. An example is the introduction of highly centralized bargaining in Norway. See discussion in Ross (1960). A step in this direction was the biggest agreement to date from 1935 ("Hovedavtalen"), often referred to as "the constitution in the Norwegian labor market" (Alsos and Jakhelln, 2022). The Norwegian Confederate of Unions (LO) aimed to participate in a more organized and comprehensive planning of society and the economy (Bals, 2021, p.320). Several studies have argued that centralized bargaining is related to fewer industrial conflicts (Moene et al., 1993, p.67).[11] One explanation of this is that, in the absence of centralized bargaining, individual unions can hope their real wage improvement can come at the expense of profits elsewhere in the economy. With centralized bargaining this is internalized and the result is wage moderation (ibid, p.68). This could further lead to fewer conflicts. I could control for the years after "Hovedavtalen" was reached with a dummy. However, this would be perfect multicolinear with the dummy

[10]The first Labor Party government only sat for 18 days, from 28. January until 15. February (The Norwegian Government, n.d.).

[11]It is however important that centralization can be measured along several dimensions. For instance, from bargaining on a firm level to a national level but each profession is separated, or bargaining on a firm level across professions. The differences are discussed in Moene et al. (1993).

that controls for whether Labor Party was in power. One could therefore interpret this dummy as a combination of both political and institutional changes.

Contracts: The large majority of conflicts happen in relation to contract negotiations. It is therefore important to control for the number of contracts that were negotiated each time period. The optimal solution would be to use the number of contracts that expired in a given time period. This is however only available for a shorter period of time between 1910 and 1920. In this period I have data that are reported on a monthly basis. This stems from the reports described earlier, published by LO (1909-1938).[12] For periods when the expiring contracts are not available, I am using the number of contracts that were revised on a yearly basis. This is at least an indication of the number of contract negotiations that took place. This is also digitized from the same reports.

Members: The total number of members in the unions is an important variable that could affect the number of industrial conflicts. Most conflicts are initiated by a union, and all the conflicts that are part of the data set are recorded by the unions. The number of members is therefore important to control for. One would expect that there is a positive relationship between the number of members and the frequency of strikes. For lockouts, the intuition is not that clear. This variable is also available from the reports published by LO.

Seasonal variation: There is seasonal variation both in the unemployment rate and the industrial conflict as displayed in figure A1.5 and A1.6 in the appendix. The pattern is especially strong for strikes. The mean estimate of the frequency of strikes is about double in the spring and summer compared to winter and fall. The variation in conflicts could stem from typical times of the year when contracts expire and negotiations take place. The pattern is similar but not as strong for lockouts. Like strikes, more lockouts take start in the spring, but the uncertainty of the estimate is much bigger.

3.5 Summary Statistics

Some summary statistics for the monthly data are displayed in table 3.2. Each observation is corresponding to a month. There is, therefore, a total of 360 observations in this data set. Descriptive statistics for the data on a yearly, union, and geographical level are available in table A1.1, A1.2 and A1.3 in the appendix.

[12] The number of expiring contracts for 1915 is taken from the report for 1913. This is done because the data is missing in the report covering 1914. This could slightly underestimate the number of expiring contracts for 1915 since some contracts may not have existed when the report was published.

The most striking feature of the data is the distribution. It is highly skewed. The average number of strikes in the period was 7.3, and the maximum number was 77. The skewness is visible in figure A1.3, and from the difference between the mean and the median. This feature of the data is even more apparent when looking at the number of lockouts. Most months went by with few employer-initiated work stoppages. The maximum number of lockouts happened at the start of the 1930s when 61 lockouts started simultaneously. The skew is apparent in all of the different data sets I am using. This feature of the data is not surprising and stems from the nature of industrial conflict. A conflict in one firm is seldom unique, and conflicts do therefore often happen at the same time. In addition, it is reasonable to believe that the organization of the workers and capital owners leads to some sort of coordination. A strike or a lockout is a powerful weapon, often with a large cost to both parties. A more coordinated effort may have a bigger impact. This feature is shown clearly in figure 3.1. The time series of the different conflicts show that the rate of conflict exploded in a few months, and was, besides these months, quite stable. It is also important to be aware of the lack of variation in the number of lockouts when evaluating the results in chapter 5. It is hard to explain any variation that is not present in the data.

One other interesting aspect of the time series in figure 3.1 is that no obvious trend is apparent. It does not look like the conflicts steadily increased or decreased in the period. The time series show a pattern, however, that can resemble some sort of seasonal variation. This is even more apparent when considering figure A1.5. Table 3.2 also shows that the unemployment rate varied substantially in the time period. From

Statistic	N	Mean	Median	St. Dev.	Min	Max
Strike	360	7.27	5	9.86	0	77
Lockout	360	1.89	1	5.17	0	61
Unemployment	360	13.18	12.10	11.05	0.30	42.40
Unemployment (Grytten)	360	4.96	4.61	3.53	0.84	14.30
Labour in power	360	0.13	0	0.34	0	1
Expired contracts	120	32.49	18.00	35.94	0.00	176.00

Table 3.2: Descriptive Statistics of Monthly Data

The table summarizes some descriptive statistics for the monthly data. Strikes are more frequent than lockouts, but the table shows that the month with the most lockouts is almost at the same level as the month with the most strikes. The data set consists of 2618 strikes and 679 lockouts. In other words, very few conflicts were lost in the merging process.

Figure 3.1: Monthly Number of Conflicts
The data set consists of more strikes than lockouts. This is visible in the time series. Several months went by without lockouts.

almost no unemployment at all, to an unemployment rate of over 40 percent. The variable "Unemployment (Grytten)" is the linear transformation of the unemployment rate discussed earlier.

Table 3.3a and 3.3b display the normal causes for strikes and lockouts as described in the reports. Each observation in the data has a description of what caused the conflict. An overview of the most usual causes from the raw material is displayed in table A1.4 and A1.5 in the appendix.

The most usual reason for a strike is demands related to contracts. This category includes both demands for a revised contract and the demand for a contract in itself. More than 60 percent of the strikes fall into this category. The second most usual reason for conflict is wage demands. These two categories make up almost 80 percent of all strikes.

The picture is different when looking at the causes of lockouts. Contract demands are still an important cause, but are relatively much less important. Explicit wage demands are almost nonexistent. Disputes over wage reduction on the other side are much more common. More than 30 percent of the lockouts in the data set stem from this. The difference compared to strikes is quite striking.

It is important to be aware of where the data stems from when analyzing these tables. The unions have their agenda, and the reason for conflict may look different if we were looking

	Cause	Freq	Relative freq
1	Contract demands	1,703	0.63
2	Wage demands	385	0.14
3	Wage reduction	112	0.04
4	Right to organize	25	0.01
5	Harassment	23	0.01
6	Other	436	0.16

(a) Summarized Causes of Strikes

	Cause	Freq	Relative freq
1	Contract demand	201	0.29
2	Wage demand	14	0.02
3	Wage reduction	224	0.32
4	Right to organize	25	0.04
5	Harassment	2	0
6	Other	227	0.33

(b) Summarized Causes of Lockouts

Table 3.3: Summarized Causes of Industrial Conflict

The tables summarizes the most usual causes of industrial conflicts as stated in the data. Panel a) summarizes the findings for strikes and panel b) is for lockouts. The most usual causes for strikes are demands related to contracts or wages. In contrast, these causes are much less common for lockouts. Wage reduction is the most frequently cited cause of lockouts in the data. The tables are created using the same method of string detection and logical statements. They should therefore be comparable. For raw data, see table A1.4 and A1.5 in the appendix.

at the employer's data. Nevertheless, I think some important insights are apparent.

The causes of strikes and lockouts seem to differ. Demands for wage reduction are closely related to lockouts. Demands for contracts, and other wage demands, seem to be more related to strikes.[13] One could view this in the context of the theory presented in section 2.4. For instance, nominal wage reduction is a demand that is more likely in periods when the firms are experiencing a lower demand. A fair assumption is that these periods also are periods with higher unemployment. In total, these differences add to the argument of distinguishing between the two forms of industrial conflict.

[13] I think it is fair to assume that the demands related to wages are demands for higher wages.

4 Method of Estimation

A major challenge of this thesis is to utilize different dimensions of the data. Due to the time period, the data material is quite limited. In addition, the data that exists is often not digitized. A large part of the work with this thesis has therefore been to identify important predictors for industrial conflict, digitize them and merge them with the original data.

Important predictors were primarily identified by existing theory as discussed in chapter 2. In addition, earlier empirical work was used. The digitization and merge process is discussed in chapter 3.

The results of this work are several equations that are possible to estimate in different specifications. The first main one is a simple pooled regression:

$$C_t = \beta_0 + \beta_1 U_t + \boldsymbol{q_t}'\boldsymbol{\delta} + \lambda_t + \epsilon_t \tag{4.1}$$

Here C_t is the frequency of industrial conflict in period t, U_t is the unemployment rate, λ_t is the time-fixed effects, and **q**' is the vector of control variables. The controls include the variables that I have discussed in section 3.4. I will use both monthly and yearly data to estimate the equation. Different controls are available for the different data sets. The equation will be estimated using ordinary least squares (OLS).

The equation is estimated with both the frequency of strikes and lockouts as the dependent variable. A significantly different estimated effect of unemployment could mean that the different forms of industrial conflict are reacting differently to the economic forces. This contributes to answering the question this thesis tries to explain.

The controls available for the monthly data are quite limited. Despite that, I am able to control for seasonal effects, yearly effects, and whether or not the Labor Party is in power. These variables are available for the whole time period. In addition, the number of expiring contracts is reported on a monthly basis in the data material between 1910 and 1920. Equation 4.1 will be estimated in different specifications to include all the controls that are available.

More controls are available when using the yearly data. In this specification, the members in the unions, the number of contracts each year, Labor Party in power dummy, and different wage variables are used. The drawback is, however, that the number of observations shrinks drastically compared to the monthly data. This will make the estimates more uncertain as the standard errors grow, all other things equal. The pooled regression is vulnerable to several threats to its validity. Some concerns are addressed and discussed in depth in section 6.

As discussed earlier, I utilize different dimensions of the data available. This makes me able to control for different fixed effects on a union/city level. As a result of the work of identifying and digitizing unemployment at different levels, I am able to use both the geographical and the union dimensions of the data. The equation looks like this:

$$C_{it} = \beta_0 + \beta_1 U_{it} + \boldsymbol{q_{it}}'\boldsymbol{\delta} + \lambda_t + \alpha_i + \epsilon_{it} \tag{4.2}$$

The subscript i denotes either the city or the union. In this specification, different measures of unemployment are used. These are discussed in section 3.2 so I will not repeat the differences. However, it is important to be aware that the scales are not the same. The estimates are therefore not comparable to the earlier estimates. The variables are on a yearly level, and the data on unemployment is only available from 1919 for the geographical specification.

The union/city fixed effects control for variables that are constant over time but are different across the units. The time-fixed effects control for the effects that are the same across units but differ over time. It is easy to imagine that unions are heterogenous and that the within and between effects would differ. In a pooled OLS regression, one must assume that these effects are equal (Bartels et al., 2008). This may be a bold assumption. It is possible to control for some of these variables if they are present in the data. However, in my case, the data is old, and finding suitable control variables may be hard and infeasible. The advantage of the fixed effects regression is that it accounts for the unobserved heterogeneity. Therefore, I do not need to observe these variables in order to control for them.

The workers are typically organized in unions specific to their occupation. For instance metal workers, bakers, and woodworkers. It is reasonable to believe that these unions have some specific characteristics that can make them more or less prone to enter a conflict. This could be an especially militant leadership in the union, different bargaining conditions, or other union-specific factors. Since many unions are industry specific I am also, at least partially, controlling for industry-specific effects. This could be consistent differences in productivity, exposure to foreign competition, and so on. The panel data structure makes me able to control for these union-fixed effects that are constant over time. It is important to underline that in a time period that extends over 30 years many of these listed factors can change drastically. The model is not able to control for any of these changes.

The geographical dimension allows me to control for many similar conditions as just discussed. Different industries are typically located in specific parts of Norway. Specific firms are also often geographically bound. The city-fixed effects could for those reasons control for some of these specific factors. It could also be reasonable to assume that the history, culture, and politics in a given place could affect the willingness to enter into a conflict or reach an agreement.

Other controls are very limited for the fixed effects regressions. The only variable I am able to control for besides the fixed effects is the number of union members in the cities/unions at a given time.

In this section, I have discussed how I utilize the data, and to the best of my abilities, isolate the effect unemployment could have on industrial conflict. The method and the resulting estimates suffer from several potential threats to its validity. Some will be addressed in chapter 6. Potential problems include omitted variable bias, measurement errors, and reversed causality. It is therefore important to underline that the results should not be interpreted as a causal effect. The data is too limited to be able to completely isolate the effect. This is however not the goal of this thesis. Hence, I do not discuss all the potential threats to a causal interpretation. The method is used to explore how the frequency of strikes and lockouts respond to different levels of the same economic variables, even though it is not possible to isolate the effect.

5 Results

5.1 The Simplest Form

I start by estimating the simplest form of equation 4.1. This is the pooled OLS with no controls. The results are displayed in table 5.1. The equation is estimated both with strike and lockout as the dependent variable. This means that the number of conflicts started each month is regressed on the unemployment rate for the same month. Columns one, two, four, and five display the estimates using the unemployment rate from Statistisk Sentralbyrå (SSB) (1948), and columns four and six are the same estimates but with the linear transformation based on Grytten (1994). The models in this section are based on monthly data.

I start by examining the results in columns one and four, the model without yearly dummies. The effect of unemployment differs significantly between the various forms of conflict. One percentage point higher unemployment rate is associated with 0.2 fewer strikes. In contrast, the same increase is associated with 0.06 more lockouts. Both estimates are significant at a one and five percent level respectively.[1] The results are in line with the theory discussed in previous sections. When examined in isolation, the results suggest that the unions respond to the level of unemployment, and utilize their increased bargaining power when unemployment is low. The estimates should be compared to the average number of lockouts and strikes in the period. The mean number of monthly conflicts for strikes and lockouts are 7.3 and 1.9 respectively. A five percentage points higher unemployment rate is associated with around one less strike.

[1]All standard errors are estimated using heteroscedasticity consistent standard errors if nothing else is noted. I have used the version known as HC3. Simulations show that this version performs best in small sample sizes (Long and Ervin, 2000). It is important to underline that the sample size with the monthly data is somewhat bigger than the threshold from the study ($N <= 250$). When estimating with yearly data, the use of these standard errors may be more critical because the number of observations is very limited.

	Dependent variable:					
	Strike			Lockout		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment	-0.198^{***}	-0.401^{***}		0.056^{**}	0.073	
	(0.046)	(0.072)		(0.022)	(0.054)	
Unemployment (Grytten)			-1.254^{***}			0.229
			(0.225)			(0.169)
Constant	9.887^{***}	6.412^{***}	7.347^{***}	1.152^{***}	0.969^{*}	0.798
	(1.060)	(1.025)	(1.099)	(0.294)	(0.514)	(0.588)
Yearly dummies	NO	YES	YES	NO	YES	YES
Observations	360	360	360	360	360	360
R^2	0.049	0.393	0.393	0.014	0.155	0.155
Adjusted R^2	0.047	0.337	0.337	0.011	0.077	0.077
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5.1: Regressions: Monthly Data, no Controls

The frequency of strikes and lockouts are the dependent variables. The unemployment rates are from Statistisk Sentralbyrå (SSB) (1948) and the linear transformation discussed in appendix A1.3. Yearly dummies are also a part of the model in columns two, three, five and six.

Table 5.1 also displays the estimates including yearly dummies. These models estimate the coefficients using the variation within each year. The effect in these models is estimated to be bigger both for lockouts and strikes. However, due to the increased standard errors, the effect of unemployment in the case of lockouts is no longer significant. A month with a five percentage points higher unemployment rate is associated with two fewer strikes. When again comparing this to the mean number of strikes, one can see that the estimated effect is not negligible, and highly significant. It is not surprising that the uncertainty about the estimates grows since much of the variation is gone in these models. However, it is interesting that for strikes, the estimate is still significant. Strikes do not just happen more frequently in years with low unemployment. It is also the case within a year with months of low unemployment.

Table 5.1 also includes the linear transformed unemployment rate. The results are displayed as the variable Unemployment (Grytten). Since the transformation is linear, only the point estimates change. The significance levels and the direction of the effects stay the same. This may be a more realistic unemployment rate, and the effect is estimated to be even bigger.

Another important insight is the amount of variance explained by the different models. Even when the yearly fixed effects are included in the model, the R^2 is only about 0.16 when the frequency of lockouts is the dependent variable. The corresponding value for the strike model is 0.39. Although a bigger R^2 is not a goal in itself, the difference is important to be aware of. Especially when expanding the models to include more controls. It is also interesting that Van der Velden (2006) found the same difference when using Dutch data.

This very simple model obviously suffers from several threats to its validity, and the estimates should be interpreted with caution. Nonetheless, it is interesting that the relationship between unemployment and industrial conflict is the opposite for strikes and lockouts in this simple model.

5.2 Adding Controls

Table 5.2 display the estimates from the same equation as table 5.1. The only difference is that I have included some control variables. Columns one, two, five and six show the estimates without and with yearly controls. The linear transformation of the unemployment rate is used as the unemployment variable in column three and seven. Column four and eight include a variable with the number of contracts that are expiring each month. This is only available between 1910 to 1920.

I start by examining the results from the strike models, specifically the two first columns of table 5.2. The estimated effect of unemployment on the frequency of strikes ranges between -0.22 and -0.28 depending on whether I include yearly fixed effects. The estimates are quite similar as in section 5.1, and still significant, at least a five percent level.

The estimates of the controls are also in line with expectations. The inclusion of seasonal effects is important. More strikes occur in the spring and the summer. The effects are highly significant. There is also a seasonal pattern in the unemployment rate.[2] This is an obvious source of omitted variable bias in table 5.1. The estimates of unemployment do, however, not change significantly after the inclusion.

In the first specification of the model, the labor in power-dummy is positive and significant. The effect disappears when including yearly dummies. It is important to underline that the time period in the sample with the Labor Party in office is quite limited, and the effect should therefore be interpreted with caution.

[2]See figure A1.5 and A1.6.

Column four displays the results when also controlling for expiring contracts. This could be a very important variable to control for as discussed in section 3.4. The number of observations shrinks substantially since this variable only is available between 1910 and 1920. The coefficient of expiring contracts is as expected positive and highly significant.

Despite the increased standard errors and limited sample size, the coefficient of the unemployment rate is still significant at a ten percent level. This specification of the model explains more than 60 percent of the variation in data. It is quite clear that the inclusion of expiring contracts is important for explaining the frequency of strikes. One could argue that the seasonal effects are capturing some of this effect since most contracts are expiring in the spring and summer. However, this approach does not capture all the variation that is present in the expiring contracts.

Columns five to eight in table 5.2 summarizes the results with lockouts as the dependent variable. The effect of unemployment is quite similar to the results without controls. Without yearly dummies, it is significant at a one percent level due to the lower standard error. The effect is estimated to be 0.07 in this specification. It is not significant when including the yearly dummies but is still estimated to be positive. This is also the case in the specification including expired contracts. The positive relationship between unemployment and lockouts is bigger than in the other models but not significant. Neither is the effect of expiring contracts. It is still important to be aware of the smaller variation of lockouts compared to strikes. This can explain some of the increased uncertainty in the estimates. As with strikes, the seasonal dummies are jointly highly significant. The pattern is also similar to the strike-models with more lockouts in the summer and spring.

Once again, the differences across the models when looking at the R^2 are striking. The models with strikes as the dependent variable consistently have a higher R^2. The variation of lockouts is in other words harder to explain with the variables in hand.

	Dependent variable:							
	Strike				Lockout			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment	-0.218^{***}	-0.278^{**}		-1.142^{*}	0.071^{***}	0.058		0.485
	(0.044)	(0.127)		(0.605)	(0.025)	(0.046)		(0.489)
Unemployment (Grytten)			-0.869^{**}				0.181	
			(0.396)				(0.142)	
Labour in power	3.798^{***}	-0.033	-0.033		-1.876^{***}	-0.151	-0.151	
	(0.947)	(2.319)	(2.319)		(0.511)	(1.026)	(1.026)	
Expired contracts				0.182^{***}				0.011
				(0.055)				(0.009)
Spring	7.473^{***}	7.579^{***}	7.579^{***}	6.589^{**}	2.608^{***}	2.631^{***}	2.631^{***}	1.546^{*}
	(1.377)	(1.263)	(1.263)	(2.898)	(0.874)	(0.896)	(0.896)	(0.913)
Summer	5.038^{***}	4.929^{***}	4.929^{***}	5.230^{**}	1.141^{***}	1.116^{***}	1.116^{***}	0.786
	(1.286)	(1.215)	(1.215)	(2.226)	(0.334)	(0.383)	(0.383)	(0.514)
Winter	0.684	0.937	0.937	3.148^{*}	0.566	0.622	0.622	0.012
	(0.781)	(1.064)	(1.064)	(1.769)	(0.533)	(0.568)	(0.568)	(0.701)
Yearly dummies	NO	YES	YES	YES	NO	YES	YES	YES
Observations	360	360	360	120	360	360	360	120
R^2	0.165	0.487	0.487	0.679	0.064	0.190	0.190	0.129
Adjusted R^2	0.153	0.434	0.434	0.636	0.050	0.105	0.105	0.013
Years in Sample	1909-1938	1909-1938	1909-1938	1910-1920	1909-1938	1909-1938	1909-1938	1910-1920
Note:	*p<0.1; **p<0.05; ***p<0.01							

Table 5.2: Regressions: Monthly Data, with Controls

Frequency of monthly strikes and lockouts are the dependent variables. Both the estimates for the unemployment rate from Statistisk Sentralbyrå (SSB) (1948) and the linear transformation are used. The models control for seasonal variation, a dummy indicating whether Labour was in power, and yearly dummies. Columns four and eight also include the number of expiring contracts. This is only available between 1910 and 1920. As a result, it is only 120 observations.

5.3 Yearly Data

Table 5.3 summarizes the results using yearly data. The unemployment rate used in this section is the one calculated by Grytten (1994). This is the actual unemployment rate he calculated, not the linear transformation used earlier. I have also included the unemployment rate from Statistisk Sentralbyrå (SSB) (1948) for comparison.

The yearly data lets me control for more and other controls with the obvious drawback of fewer observations. The second, third fifth and sixth columns include variables controlling for changes in wages in previous periods in addition to the number of union members, agreements reached each year, and a dummy variable indicating whether the Labor Party is in power. Since the models with wages are utilizing changes, additional observations are not available.

Despite the dramatically reduced number of observations, and increased standard errors, the relationship between unemployment and the different forms of industrial conflict stay the same. For strikes, it is negative and significant at a five and one percent level. Lockouts are positively related to unemployment and are significant at a ten and five percent level. It is an important insight that even with very limited data material strikes and lockouts seem to react significantly differently to changes in economic conditions. The coefficients are much larger compared to the ones estimated with the monthly data. For instance, columns one and four display coefficients of -18.9 and 5.2. This must be interpreted in light of the increased average of conflicts. The yearly mean of strikes and lockouts is 87 and 23 respectively.

Unsurprisingly, the coefficients estimated with the unemployment rate from Statistisk Sentralbyrå (SSB) (1948) are smaller. This stems from the larger variation in unemployment in the period according to the SSB data.[3] The signs of the estimates are still the same as before, and the estimates are still significant at a five percent level. None of the other estimates change much as a result of the different unemployment rates.

Both members and the number of reports control for the general prevalence of unions in the Norwegian labor market in the period.[4] When including wage variables, both estimates are positive but not significant for strikes. Members are interestingly negatively related to lockouts in the same specification. The change in real wages the previous year is significant in both models.

[3] See figure A1.1 for a comparison of the two different measures.

[4] The number of members also control for the union power in the bargaining process.

The effect of lagged change in the real wage is estimated to be positive and significant for both lockouts and strikes. This is not in line with the theory from for instance Ashenfelter and Johnson (1969). Since this relationship is not the focus of this thesis I do not discuss this extensively. However, one could argue that the changes in wages in previous periods could boost the expectations of the union, and therefore also the wage demand. In addition, I have only used the change in the last period. The dynamics may be more complex than this.

Another key insight from these results is that even without yearly dummies, and seasonal variation, the models are able to explain a big part of the variation in dependent variables. In this case, this is also true when considering lockouts. As before the R^2 is smaller compared to the strike-models, but much bigger compared to the models previously discussed.

	Dependent variable:					
	Strike			Lockout		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment (Grytten)	-18.937^{**}	-13.194^{***}		5.240^{*}	7.372^{**}	
	(7.672)	(4.261)		(2.639)	(2.834)	
Unemployment (SSB)			-4.064^{**}			1.945^{**}
			(1.454)			(0.909)
Members/1000	1.711	0.473	0.395	-0.394	-0.736^{*}	-0.583
	(1.002)	(0.400)	(0.431)	(0.325)	(0.374)	(0.484)
Contracts	-0.033	0.017	0.029	0.019	0.030	0.019
	(0.060)	(0.039)	(0.040)	(0.017)	(0.021)	(0.025)
Labour in power	-175.120	-50.613	-58.480	5.839	46.403	42.072
	(122.024)	(71.510)	(91.274)	(29.037)	(39.088)	(50.973)
$\Delta Realwage_{t-1}$		2.970^{**}	2.946^{**}		0.709^{**}	0.654^{*}
		(1.235)	(1.218)		(0.340)	(0.371)
Decreasing wage		2.014	0.103		-10.535	-8.876
		(14.332)	(16.853)		(14.709)	(16.783)
Constant	18.365	85.186^{***}	75.465^{**}	30.524^{*}	52.746^{**}	53.268^{*}
	(44.364)	(29.163)	(30.662)	(16.502)	(22.760)	(29.894)
Observations	30	27	27	30	27	27
R^2	0.474	0.661	0.662	0.286	0.470	0.372
Adjusted R^2	0.390	0.559	0.561	0.172	0.310	0.183
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5.3: Regressions: Yearly Data with Controls

The frequency of yearly strikes and lockouts are the dependent variables. The unemployment rate calculated by Grytten (1994) is used in this specification. In addition, I have added the yearly average unemployment rate from Statistisk Sentralbyrå (SSB) (1948). The controls that stem from LO (1909-1938) are members and the number of contracts revised. The wages are from Statistisk Sentralbyrå (SSB) (1948) and inflation is from Statistisk Sentralbyrå (SSB) (2017). The members are given in 1000s.

5.4 City and Union Fixed Effects

The last results I present are the models controlling for city and union fixed effects. The available controls are limited. The only control variable used in these models, in addition to fixed effects, is the number of unionized workers in each city or union. As a result, many potential determinants are not a part of the models presented in this section. It is also important to be aware of the unemployment measure used when interpreting the models. The measure is either on a union- or a city-level which can have implications for the interpretation. This is discussed in chapter 6. All standard errors in this section are clustered on either the city or the union.

Table 5.4 contains the estimates of the fixed effects regression using the geographical dimension. Columns two, three, five, and six do not have observations from 1919 because the member data is missing from this year. All the different specifications are controlling for city-fixed effects, but only the third and sixth include time-fixed effects. Since unemployment is in absolute figures, the estimates are presented per 1000. Recall that this unemployment measure captures the number of inquiries to the public job placement offices in each city.

	Dependent variable:					
	Strike			Lockout		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment/1000	-0.06^{**}	-0.19^{***}	-0.16^{***}	0.00	0.02^{**}	0.03^{***}
	(0.02)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)
Members/1000		0.56^{***}	0.52^{***}		-0.08^{***}	-0.08^{***}
		(0.04)	(0.03)		(0.01)	(0.01)
City FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	YES
Num. obs.	360	342	342	360	342	342
Num. groups: City	18	18	18	18	18	18
Num. groups: Year			19			19
R^2 (full model)	0.40	0.71	0.78	0.24	0.31	0.44
Adj. R^2 (full model)	0.37	0.69	0.76	0.20	0.27	0.38

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 5.4: Fixed Effects: Big Cities

The table displays the results from the fixed effects regressions using the 18 biggest cities. The unemployment variable is in absolute numbers. Standard errors are estimated using heteroscedastic and autocorrelation robust. They are clustered on cities. The time period for this model is 1919-1938. In addition, the observations from 1919 are lost when I control for members since I do not have member-data on a geographical level for this year.

The estimates show a similar pattern as before. Unemployment is estimated to be negatively associated with strikes, and significant at least at a five percent level in all the specifications of this model. The interpretation is that 1000 more inquiries are associated with 0.16 fewer strikes when using the coefficient from column three. When comparing to the mean value of 2.35 strikes, and 17882 annual inquiries in table A1.3, the estimated effect is not negligible. For instance, if the unemployment measure rose from 15000 to 25000, the model is predicting 1.6 fewer strikes.

For lockouts, the effect is smaller but significant at a five percent level when controlling for members, and at a one percent level when also including yearly fixed effects. The effect is estimated to be positive. One should, however, be cautious when interpreting these results.

As discussed in section 3.2, this unemployment measure does not account for changes in the workforce. Two possible assumptions are possible to make in order to use this measure as an unbiased estimate of unemployment. First, the size of the workforce was constant during the period. This is however not reasonable as previously discussed. Second, the share of union members in each city is the same. When controlling for union members, this would also control for the changes in population. Despite this being a more plausible assumption, it is not convincing. Different cities have different industries and labor markets. A city with a more traditional industry may be expected to have a higher share of union members compared to a city with more service industries. I have therefore tried to correct this.

Table 5.5 includes estimates where the unemployment measure is divided by the annual population in each city.[5] The results are similar to before. For strikes, the effect is estimated to be negative and significant both with and without controlling for members. Since the measure is different the effect is not directly comparable to the ones in table 5.4. For instance, in column one the coefficient of unemployment is estimated to be -4. If the number of inquiries increases from 15000 to 25000 and the population is at 40000, the model predicts about one less strike. The effect is still negative but not estimated to be significant when also controlling for yearly fixed effects. In this specification, the relationship between unemployment and lockouts is never significant.

Finally, I have estimated the model with union fixed effects. The results are summarized in table 5.6. Recall that the unemployment rate used in this model is at a union level. It

[5] This transformation of the unemployment measure, however, also includes some assumptions that may not hold. These are discussed in section 3.2, and are important to be aware of when interpreting the results.

	Dependent variable:					
	Strike			Lockout		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment (Pop Adj)	-4.01^{***}	-3.95^{**}	-1.38	-0.06	0.00	0.24
	(1.21)	(1.67)	(1.34)	(0.17)	(0.29)	(0.43)
Members/1000		0.34^{***}	0.31^{***}		-0.05^{***}	-0.04^{***}
		(0.02)	(0.01)		(0.00)	(0.00)
City FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	YES
Num. obs.	360	342	342	360	342	342
Num. groups: City	18	18	18	18	18	18
Num. groups: Year			19			19
R^2 (full model)	0.41	0.58	0.69	0.24	0.29	0.42
Adj. R^2 (full model)	0.38	0.55	0.66	0.20	0.25	0.35

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 5.5: Fixed Effects: Big Cities with Population Adjustment

The table displays the results from the fixed effects regressions where the unemployment is adjusted for the population size of the cities. Between 1920-1930 these figures are from Statistisk Sentralbyrå (SSB) (1919-1938). After 1930, I assumed that the share of the Norwegian population living in the cities are constant. The population of Norway is from Statistisk Sentralbyrå (SSB) (2023). Standard errors are estimated using heteroscedastic and autocorrelation robust standard errors. They are clustered on cities.

can be interpreted as the average percentage of a year a union member is unemployed.

The pattern discussed in earlier models is yet again present, at least when not including the yearly fixed effects. Higher unemployment in the unions is associated with fewer strikes. This means that when controlling for the union-specific features, the relationship is estimated to be negative. The estimate is, however, not significant when including yearly fixed effects. None of the coefficients of unemployment for the lockout models are significant. It is important to notice that even though there are more observations, new conflicts are not created. The conflicts are just distributed on more observations. The variation of lockouts is therefore quite limited. The coefficient for the number of members is positive and significant for the strike models, and negative for the lockouts, although not significant when including yearly fixed effects.

To sum up, the results in this section showed a similar pattern as before. The frequency of strikes is estimated to be negatively associated with unemployment. This is the case for all the models estimated. The estimates are however not significant in all the specifications.

For lockouts, the estimates are even more uncertain. Most of the estimates are not estimated to be significant at all. Several factors can explain the less precise estimates displayed in this section. First, as discussed in section 3.3 fewer conflicts are a part of the data sets used for these models. This increases the uncertainty. Second, the fixed effects introduce more parameters to be estimated. The fixed effects are only able to control for factors that are constant either across time or across the cities/unions. If the explanatory power of these factors is limited in combination with the increased number of parameters, this can cause less precise estimates. Third, the included fixed effects do capture some effects that are not captured by the other models, and the relationship is in reality not significant. In addition, the different unemployment measures may have an effect. This is discussed in the next section. Before I move on to the discussion, is interesting to note that the results displayed in this section show yet again that more of the variation of strikes is explained by the models compared to lockouts. This is consistently the case for all models estimated in this chapter.

	Dependent variable:			
	Strike		Lockout	
	(1)	(2)	(3)	(4)
Unemployment	-0.240^{**}	-0.103	0.009	-0.032
	(0.089)	(0.106)	(0.030)	(0.030)
Members/1000	1.7453^{**}	1.8515^{***}	-0.0799^{**}	-0.0346
	(0.6091)	(0.5967)	(0.0369)	(0.0342)
Union FE	YES	YES	YES	YES
Year FE	NO	YES	NO	YES
Num. obs.	412	412	412	412
Num. groups: Union	17	17	17	17
R^2 (full model)	0.547	0.634	0.180	0.352
Adj. R^2 (full model)	0.526	0.587	0.143	0.268
Num. groups: year		30		30

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 5.6: Fixed Effects: Unions

The unemployment rate used is from LO (1909-1938). It can be interpreted as the percentage of the year the average worker went unemployed. In addition to fixed effects, I am able to control for the members in each union each year. Standard errors are estimated using heteroscedastic and autocorrelation robust standard errors. They are clustered on unions.

6 Discussion

The previous chapter summarized the results from estimating the equations in chapter 4. All the models tried to answer how the frequency of industrial conflict reacts to unemployment, and if the effect is different for lockouts and strikes. This chapter compares the results and discusses the interpretations of the different models. It is necessary to devote space to answer important questions about what is possible to conclude using the results in hand. And, not least, what the limitations are. Is it possible to use the results to say something about the relationship between industrial conflict and unemployment? Does it differ for strikes and lockouts? The answer is nuanced.

First, the simplest and most important insights are found using the simplest models. The results from table 5.1 are instructive despite the simplicity of the model. In this time period, the relationship differs between strikes and unemployment, and lockouts and unemployment. Unemployment and the frequency of strikes are negatively associated while it is positive for lockouts. This difference is interesting in itself. Although this model is not answering many important questions, it is underlining one key point. Something causes this difference. It may not be unemployment directly, but this result suggests that different forms of industrial conflict should be analyzed separately.

The different estimates are robust to several changes to the model. The general pattern of negative point estimates for strikes and positive point estimates for lockouts holds true for almost every model. The results for lockouts are generally less precisely estimated compared to strikes. This is not surprising given that fewer lockouts are part of the data material.

The negative relationship between strikes and unemployment aligns with the theory presented in chapter 2. A lower unemployment rate can induce the union to choose a strategy that leads to conflict. The result is also in line with earlier empirical research done in other countries and other periods. The positive relationship between unemployment and lockouts that one observes in some of these models could also partially be explained by the theory. Lockouts seem to be less attractive for firms when the unemployment rate is low. It is interesting that Van der Velden (2006) found a similar pattern using Dutch data. As in his paper, my models consistently explain more of the variation in the frequency of strikes compared to lockouts. This result shows that the forces leading to lockouts may be different from strikes. New theory and empirical work are necessary to fully understand what makes lockouts more likely.

One may ask if it is possible to conclude that the differences stem from the causal effect of unemployment? No, it is not. For instance, the obvious risk of omitted variable bias is present in every model presented. However, this will always be the case when using this kind of data. Interpreting the results in combination with the theory presented in chapter 2 and earlier empirical work, points in the direction of unemployment as an important variable when analyzing industrial conflict. Even though the estimates do not have a strict causal interpretation some problems still need to be addressed. The discussion can also hopefully help explain the different estimates between the models. The different data sets used in this thesis contain the same conflicts. New conflicts do not emerge, the conflicts are just combined in different ways. All the models are thus vulnerable to many of the same problems.

The control variables available are limited. Some variables are not available for every specification but could be vital for the explanatory power. For instance, the model using the yearly data is able to control for most variables. In this specification, the estimates are significantly different from each other at any meaningful level. Table 5.3 shows that including the wage variables increases the significance level of both estimates. Wage is an example of a control that I was not able to use in the other models. Another example is control of monthly expiring contracts. This is only available for a limited time period. However, at least for strikes, the coefficient is highly significant. I am not able to control for this variable in the other specifications of the models.

The difference in controls could in other words help explain why the effect of unemployment is estimated to be different for strikes and lockouts in some models and not in others. Some variables like the financial position of the unions; institutional or political changes; or profits for the firms have I not been able to control for at all. Large historical, political, or cultural changes that happened in the period have not been explored in this thesis either.

The times series of industrial conflict displayed in figure 3.1 shows that some months involve large outliers both for strikes and lockouts. Variables that actually caused these events, but are not a part of my model are an obvious concern.

Figure 6.1 partly addresses this concern. The figure shows the estimated coefficient for unemployment when removing one year at a time from the sample. The specification

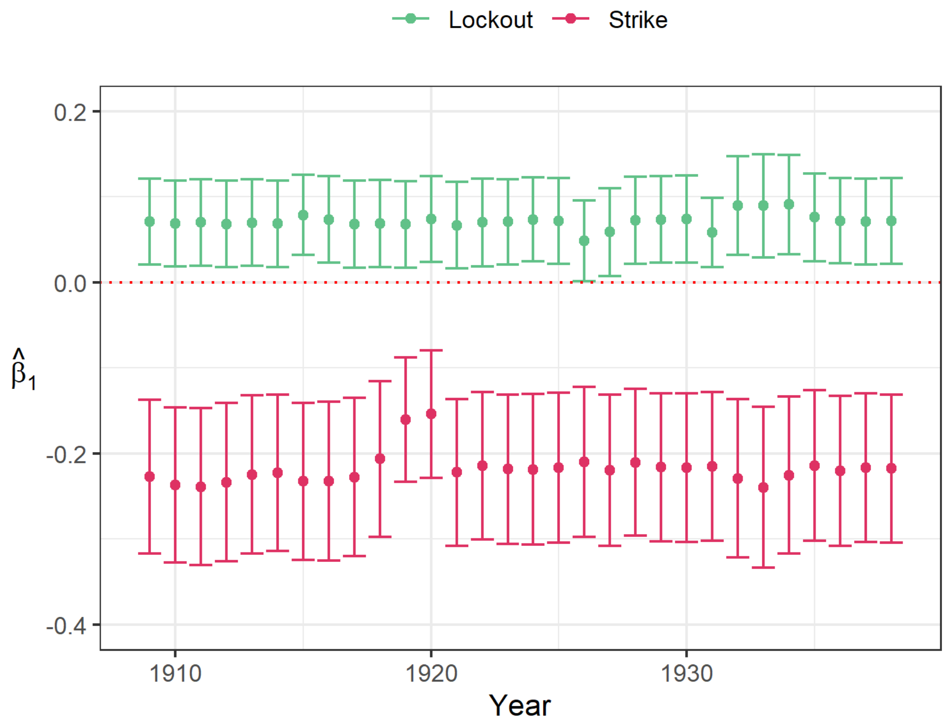


Figure 6.1: Effect of Removing Outliers

The figure shows the estimated β_1 when removing one year at the time. The estimated regression is: $C_t = \beta_0 + \beta_1 U_t + \beta_2 Seaon_t + \beta_3 Labor_t + \epsilon_t$. This is the same regression as the one displayed in columns one and five in table 5.2. The frequency of monthly conflicts is the dependent variable with seasonal controls, as well as the Labor Party dummy. The x-axis displays the year that is removed when estimating the regression, and the y-axis is the estimated effect. The results are displayed with a 95 percent confidence interval. All estimates are still estimated to be significant at this level.

is the same as the regression estimated in columns one and five in table 5.2. One can argue that a significant result vulnerable to removing a few numbers of observations is less convincing. The x-axis shows the removed year. For instance, the estimated effect corresponding to the year 1920 is the β_1 estimated without the observations from this year.

As the figure shows, the estimates are quite robust from removing observations. The sign does not change for any estimates, and the effect is always estimated to be different for strikes and lockouts, respectively. At the same time, it is obvious that removing some particular years do have an effect. For strikes, the biggest change in the point estimate happens when observations from 1919 or 1920 are removed. These are years with an exceptional amount of strikes. For lockouts, removing 1926 and 1931 does have some impact. These are also years with many lockouts. The estimated effect is just significant when observations from 1926 are removed. All in all, however, the estimates reported in table 5.2 are not depending on observations from one particular year to be significant. If it is meaningful to remove years from the sample at all is a valid question. There is a reason why many conflicts happened in those years, and unemployment may be an important part of it. However, if the results were not robust to small changes in the sample, it would be less convincing that unemployment actually plays an important role.

Another important factor that accounts for the differences between the models is the unemployment rate that is used. The unemployment rate is observed at different levels. When estimating the models with union- and city-fixed effects, the unemployment rate is at a union level or a city level. When analyzing the bargaining problem, this does not have the exact same implications as in the models using a national unemployment rate. One could argue that unemployment at the union level is important because the unions in large part cover different industries. This means that the unemployment rate could be considered an unemployment rate at an industry level.

In the framework of the asymmetric information model from Moene (2015) presented earlier, lower unemployment within the union could mean that the union perceived the probability of the firm being in a good state as higher. Resulting in a higher probability of a strike. However, at the same time the unemployment rate in other unions, and the labor market in general, should also have an impact on the unions' perception. The picture is in other words complicated.

Much of the same logic also holds true for the unemployment observed at a city level. The labor market is not restricted to the city. Unemployment rates in neighboring cities or other parts of the country could also make a difference for the unions and employers. In addition, since this measure of unemployment is from offices that only were available in cities, it is reasonable to believe that they also attracted people not living in the cities but nearby. The conflicts used in this model only include conflicts that took place in the city where the office was located. This is also a concern.

The important takeaway is that when measuring unemployment on different levels, I am not comparing the exact same dynamics. It is fair to assume that there is a transaction cost in moving to another place for work or changing occupation and therefore union. However, unemployment in one city or union is part of a bigger labor market. When analyzing the observations in isolation, one can lose this dynamic. The effects are therefore expected to be somewhat different between the models, and this is important to be aware of.

Despite the concerns discussed, the results in this thesis suggest that the frequency of strikes and lockout react differently when faced with the same economic conditions. The estimates become more uncertain when controlling for more variables. More controls are generally considered an advantage. However, in this setting where many variables will be impossible to control for anyway, and where any causal effect is hard to establish, introducing too many variables can lead to noise in the estimates. This is especially true with correlated variables. A different research design is needed to isolate the effect of unemployment. Thus, one should interpret the estimates in this thesis with caution, but also be cautious about analyzing every different form of industrial conflict as the same thing.

7 Conclusion

In this master thesis, I have explored the relationship between unemployment and industrial conflict, and specifically, if the relationship is different for the frequency of strikes and lockouts. The questions are answered using Norwegian data between 1909 and 1938.

To form some hypotheses about the relationship I first introduced some different theories aiming to explain industrial conflict. The model from Moene (2015) showed that asymmetric information can play a role in the bargaining setting, and different forms of private information can lead to different outcomes. It underlines that the probability of a strike or a lockout can be affected by different forces. The influential model from Ashenfelter and Johnson (1969) incorporated unemployment as an important determinator of industrial conflict. I then showed how the unemployment rate can affect the frequency of industrial conflict. The important takeaway was that the frequency of strikes and lockouts may respond differently to different levels of unemployment. Both theoretical and earlier empirical work suggest that lower unemployment leads to more strikes. The picture for lockouts is more unclear. I also showed that earlier empirical work has largely not separated between strikes and lockouts. With this in mind, most empirical studies find a negative relationship between industrial conflict and unemployment.

How the data were collected, and the pitfalls in this process, were then presented. In order to test the theory, a lot of work has been put into digitizing relevant data from sources that were not always easily accessible. I also discussed the different measures of unemployment that were used and how they could influence the results before I outlined the method used to estimate the results.

The results showed that there is a negative relationship between the frequency of strikes and unemployment in the data. The relationship is the opposite for the frequency of lockouts. It is important to underline that the results were not significant in all of the estimated models. However, this is still an interesting result that should be examined more in-depth in the future. The negative relationship between strikes and unemployment is in line with both theory and earlier empirical work. The positive relationship between lockouts and unemployment, however, is less studied. I have discussed some of the weaknesses of the results in chapter 6. These weaknesses emphasize the need for further exploration of the forces that affect the different forms of industrial conflict.

The theory from Moene (2015) shows that a theoretical distinction is useful. Further work should focus on operationalizing this theory, or similar frameworks that distinguish between strikes and lockouts, into equations of observable variables. To estimate these equations, new data is needed in order to separate between strikes and lockouts. The data used in this thesis is suitable to serve as a basis for future work. In combination with partly undigitized data, new empirical research using microdata is possible.[1] The undigitized data is available on a firm level and contains information about each negotiated contract. It is present in the same reports that formed the basis for this thesis. Variables such as wage, work hours, and vacation are a part of this data set. Combining this with the data used in this thesis will result in a larger and more detailed data set. As a result, much more accurate estimates are possible.

For now, it is clear that distinguishing between different forms of industrial conflict can be fruitful. The results in this thesis are not conclusive in determining whether the unemployment rate is causing the differences. New research is needed for establishing the causal effects.

[1] I am in the process of digitizing this data at this moment as a research assistant. However, I was not able to complete this work in time to include the data in this thesis.

Bibliography

Alsos, K., & Jakhelln, H. (2022). *Hovedavtale* [Accessed: 2023-01-30]. http://snl.no/hovedavtale

Ashenfelter, O., & Johnson, G. E. (1969). Bargaining theory, trade unions, and industrial strike activity. *The American Economic Review*, *59*(1), 35–49.

Bals, J. (2021). *Streik!: En historie om strid, samhold og solidaritet*. Res publica.

Bartels, B., et al. (2008). Beyond" fixed versus random effects": A framework for improving substantive and statistical analysis of panel, time-series cross-sectional, and multilevel data. *The Society for Political Methodology*, *9*, 1–43.

Det Statistiske Centralbyrå. (1922). *Folketellingen i Norge. 1 desember 1920. Folkemengde og areal i Rikets forskjellige deler. Hussamlinger på landet.* (D. S. Centralbyrå, Ed.).

Farber, H. S. (1978). Bargaining theory, wage outcomes, and the occurrence of strikes: An econometric analysis. *The American Economic Review*, *68*(3), 262–271.

Gjerløw, H., & Rasmussen, M. B. (2022). Revolution, elite fear, and electoral institutions. *Comparative Politics*, *54*(4), 595–619.

Grytten, O. H. (1994). En empirisk analyse av det norske arbeidsmarked 1918-1939 arbeidsledigheten i norge i internasjonalt perspektiv. *Doctoral dissertations 1953-1998 Norges Handelshøyskole*.

Hamark, J. (2022). Strikes and lockouts: The need to separate labour conflicts. *Economic and Industrial Democracy*, *43*(4), 1891–1910.

Hayes, B. (1984). Unions and strikes with asymmetric information. *Journal of Labor Economics*, *2*(1), 57–83.

Hibbs, D. A. (1987). The political economy of industrial democracies. In *The political economy of industrial democracies*. Harvard University Press.

Hicks, J. (1963). *The theory of wages* (2nd edition). Macmillian & Co Ltd.

Hlavac, M. (2018). *Stargazer: Well-formatted regression and summary statistics tables* [R package version 5.2.2]. Central European Labour Studies Institute (CELSI). Bratislava, Slovakia. https://CRAN.R-project.org/package=stargazer

International Labour Organization. (1993). Resolution concerning statistics of strikes, lockouts and other action due to labour disputes, adopted by the fifteenth international conference of labour statisticians [Accessed: 2023-02-27].

Kennan, J. (1986). The economics of strikes. In R. Layard & O. Ashenfelter (Eds.), *Handbook of labor economics* (pp. 1091–1137). Elsevier.

Leifeld, P. (2013). texreg: Conversion of statistical model output in R to LaTeX and HTML tables. *Journal of Statistical Software*, *55*(8), 1–24. http://dx.doi.org/10.18637/jss.v055.i08

LO. (1909-1938). Beretninger fra landsorganisasjonen (lo) (LO, Ed.) [All the different reports between 1909 and 1938 are utilized in making the data set for industrial conflict.].

Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity consistent standard errors in the linear regression model. *The American Statistician*, *54*(3), 217–224.

Moene, K. O. (2015). The Bargaining Society: An essay in memory of LJ. *Nordic Journal of Political Economy*, *40*.

Moene, K. O., Wallerstein, M., & Hoel, M. (1993). Bargaining structure and economic performance. In R. J. Flanagan, K. O. Moene & M. Wallerstein (Eds.), *Trade union behaviour, pay-bargaining, and economic performance*. Oxford University Press.

Mori, S., Suen, C. Y., & Yamamoto, K. (1992). Historical review of ocr research and development. *Proceedings of the IEEE*, *80*(7), 1029–1058.

O'Brien, F. S. (1965). Industrial conflict and business fluctuations: A comment. *Journal of Political Economy*, *73*(6), 650–654.

Ooms, J. (2021). *Magick: Advanced graphics and image-processing in r* [R package version 2.7.3]. https://CRAN.R-project.org/package=magick

Ooms, J. (2022a). *Pdftools: Text extraction, rendering and converting of pdf documents* [R package version 3.2.1]. https://CRAN.R-project.org/package=pdftools

Ooms, J. (2022b). *Tesseract: Open source ocr engine* [R package version 5.1.0]. https://CRAN.R-project.org/package=tesseract

Paldam, M., & Pedersen, P. J. (1982). The macroeconomic strike model: A study of seventeen countries, 1948–1975. *ILR Review*, *35*(4), 504–521.

Pencavel, J. H. (1970). An investigation into industrial strike activity in britain. *Economica*, *37*(147), 239–256.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861-1957. *economica*, *25*(100), 283–299.

Rees, A. (1952). Industrial conflict and business fluctuations. *Journal of Political Economy*, *60*(5), 371–382.

Ross, A. M. (1960). Changing patterns of industrial conflict. *Monthly Labour Review*, *83*, 229–242.

Sandvik, O. (2020). *Hvorfor ulike arbeidsledighetstall?* [Accessed: 2023-02-28]. https://www.ssb.no/arbeid-og-lonn/artikler-og-publikasjoner/hvorfor-ulike-arbeidsledighetstall--410344

Smith, R. (2007). An overview of the tesseract ocr engine. *Ninth international conference on document analysis and recognition (ICDAR 2007)*, *2*, 629–633.

Statistisk Sentralbyrå (SSB). (1948). Statistiske oversikter 1948. norges offisielle statistikk. x. 178 (S. Sentralbyrå, Ed.).

Statistisk Sentralbyrå (SSB). (2017). *11452: Konsumprisindeks, historisk serie (1998=100) (avslutta serie) 1865 - 2016* [Accessed: 2023-04-16]. https://www.ssb.no/statbank/table/11452/

Statistisk Sentralbyrå (SSB). (2023). *05803: Endringer i befolkningen i løpet av året 1735 - 2023* [Accessed: 2023-04-13]. https://www.ssb.no/statbank/table/05803

Statistisk Sentralbyrå (SSB). (1919-1938). Statistiske årbøker for norge [Yearly reports published by SSB. I have used data from reports between 1919 to 1938]. https://www.ssb.no/befolkning/artikler-og-publikasjoner/statistisk-aarbok?start=60

The Norwegian Government. (n.d.). *Christopher hornsruds regjering* [Accessed: 2023-01-30]. https://www.regjeringen.no/no/om-regjeringa/tidligere-regjeringer-og-historie/sok-i-regjeringer-siden-1814/historiske-regjeringer/regjeringsliste-1905-1945/christopher-hornsruds-regjering-1928/id507322/

Van der Velden, S. (2006). Lockouts in the netherlands: Why statistics on labour disputes must discriminate between strikes and lockouts, and why new statistics need to be compiled. *Historical Social Research/Historische Sozialforschung*, 341–362.

A1 Math, Tables and Figures

A1.1 Model from Moene

Strike: The inequality $E(w) > \tilde{w}$ must hold for the union to choose the aggressive strategy.

$$\begin{aligned} (1-s_w)\alpha R + (1-\alpha)q &> \alpha\theta R + (1-\alpha)q \\ (1-s_w)\alpha R &> \alpha\theta R \\ \frac{(1-s_w)\alpha R}{\alpha R} &> \frac{\alpha\theta R}{\alpha R} \end{aligned} \tag{A1.1}$$

After simplification, we, therefore, end up with the simple inequality:

$$(1-s_w) > \theta \tag{A1.2}$$

The aggressive strategy is more attractive if the probability for good conditions is high relative to θ.

Lockout: On the other hand, when the union has private information, the firm will choose an aggressive strategy when $E(\pi) > \pi^*$.

$$\begin{aligned} (1-s_l\beta)R - (s_l(1-\beta)q + (1-s_l)q_0 &> R - (1-\beta)q \\ S_l\beta q - s_l q - q_0 + s_l q_0 + q - \beta q &> s_l\beta R \end{aligned} \tag{A1.3}$$

We simplify to get the inequality:

$$(1-s_l)((1-\beta)q - q_0) > s_l\beta R \tag{A1.4}$$

A1.2 Model from Ashenfelter and Johnson

The wage increase that is acceptable for the members of the union is by definition:

$$y_A \equiv \frac{\Delta W}{\tilde{W}} \tag{A1.5}$$

ΔW is the absolute wage increase and $\tilde{W}$ is the previous wage rate. The model assumes that the wage increase is a decreasing function of the length of the strike.

$$\begin{aligned} y_A &= v(S) \\ \text{Where: } \frac{\delta y_A}{\delta S} &< 0 \end{aligned} \tag{A1.6}$$

Ashenfelter and Johnson represent this relationship as

$$y_A = y_* + (y_0 - y_*)e^{\tau S} \tag{A1.7}$$

The firm maximizes its future profit stream. The profit level in each time period is defined as:

$$\begin{aligned} \pi &= \alpha P - \beta W - H \\ \text{Where: } W &= \tilde{W}(1 + y_A) \end{aligned} \tag{A1.8}$$

After substitution and integration, the present value function of the firm becomes

$$V = (\alpha P - \beta \tilde{W}(1 + y_* + (y_0 - y_*)e^{-\tau S}))\frac{e^{-\tau S}}{r} - \frac{H}{r} \tag{A1.9}$$

This is depending only on the length of the strike. The firm, therefore, decides whether it agrees to the initial demand of the union, y_0, or if a work stoppage that will result in a lower wage is worth it. The dilemma for the firm is even easier to illustrate when we differentiate and solve for S.

$$S = -\frac{1}{\tau} \times ln\left[\frac{\alpha P - \beta \tilde{W}(1 + y_*)}{\beta \tilde{W}(1 + \frac{\tau}{r})(y_0 - y_*)}\right] \tag{A1.10}$$

For a strike to happen, $S > 0$, the following inequality must be satisfied:

$$y_0 > \frac{\alpha P - \beta \tilde{W}(1 - \frac{\tau}{r} y_*)}{\beta \tilde{W}(1 + \frac{\tau}{r})} \tag{A1.11}$$

According to this model, a strike is more likely to happen the bigger y_0 and τ are. On the other hand, a conflict is less likely to occur the greater P, $\frac{\alpha}{\beta}$, r, and y_* are.

A1.3 Measure of Unemployment

According to Grytten, the estimates from SSB are overestimating the true unemployment. I will here present some of the arguments of Grytten. The unemployment rate from SSB is estimated using ten unions. The members from these unions accounted for only around seven percent of the total workforce in 1939 (Grytten, 1994, p.45). The unions that are used to create the unemployment measure mainly organized workers in industry and construction. Grytten argues that these are sectors that are very sensitive to market fluctuations. The data does not include "secure" jobs in the public sector, or in agriculture. In addition to this, the members of these unions got compensated when unemployed. This is not the case for unorganized workers before 1938 (Ibid, p.47). These arguments indicate that the unions may not be representative of the Norwegian workforce during the period.

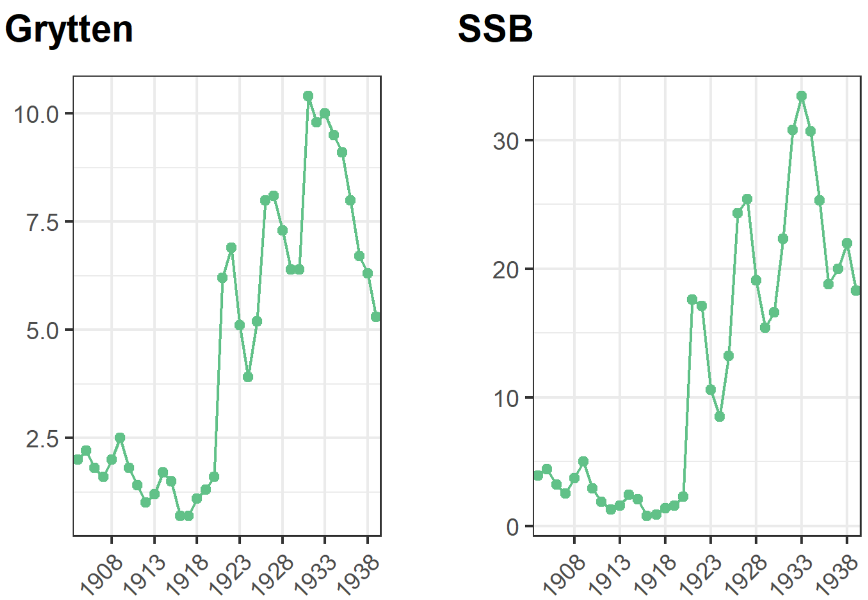


Figure A1.1: Grytten versus SSB: Yearly Time Series of Unemployment

The yearly series of the unemployment rate of Grytten and SSB. They show a similar pattern, but there are some differences. Note that the series goes further back than this thesis.

Grytten uses the observed unemployment to estimate new unemployment rates. I will not go into detail about his method, but the main point is that his estimates are significantly lower than the ones from SSB. The two different time series are plotted in figure A1.1. Except for the scale, they look very similar. This is even more apparent when the two different estimates are plotted against each other.

Figure A1.2 shows the two different unemployment estimates of SSB and Grytten that are used in this thesis plotted against each other. The relationship can be modeled with a linear model. One can also see that the two different measures are very correlated. It is actually close to one.

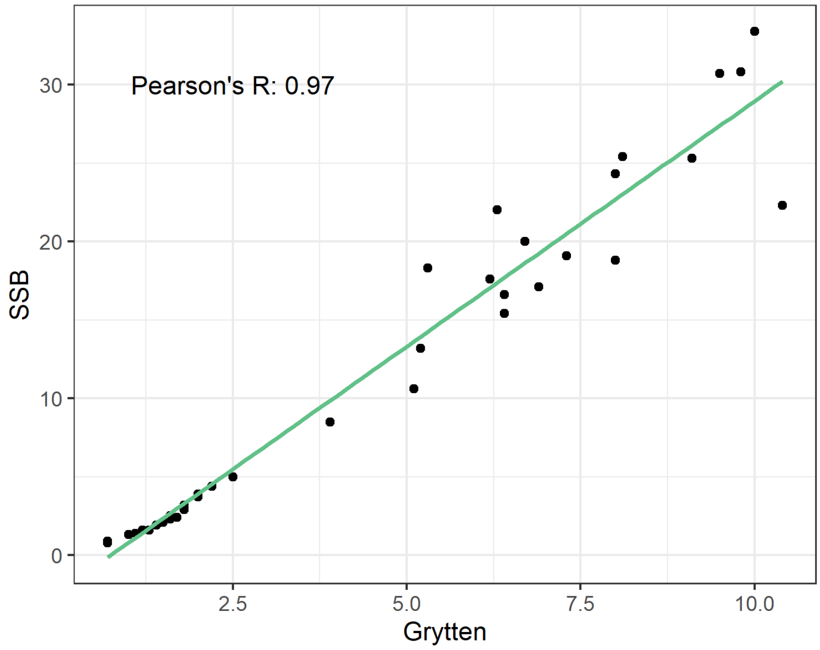


Figure A1.2: Relationship between Grytten's and SSB's Estimates of Unemployment
The figure displays the yearly unemployment rate estimates of Grytten (1994) and Statistisk Sentralbyrå (SSB) (1948) plotted against each other. There is a strong correlation between the estimates. The figure also displays the linear relationship.

The linear transformation used in this thesis is based on the linear relationship that looks to be apparent between the estimates of Grytten (1994) and Statistisk Sentralbyrå (SSB) (1948). The estimated relationship looks like:

$$U_{SSB} = -2.23 + 3.128 U_{Grytten} \tag{A1.12}$$

The linear transformation of the unemployment variable is therefore given by:

$$U_t = \frac{2.332 + U_{SSB}}{3.128} \tag{A1.13}$$

A1.4 Tables and Figures

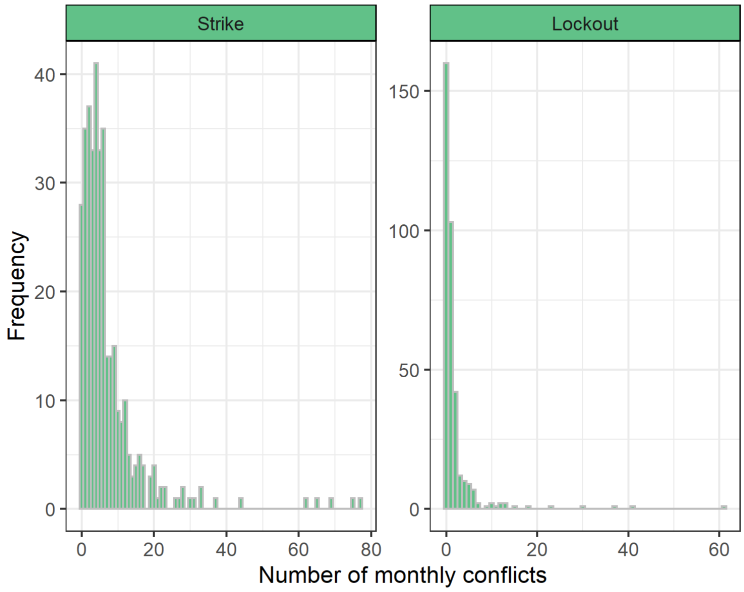


Figure A1.3: Distribution of Monthly Conflicts

The distribution of monthly conflicts is highly right-skewed. It is apparent for both lockouts and strikes. It is worth noting that most months went by with very few lockouts starting.

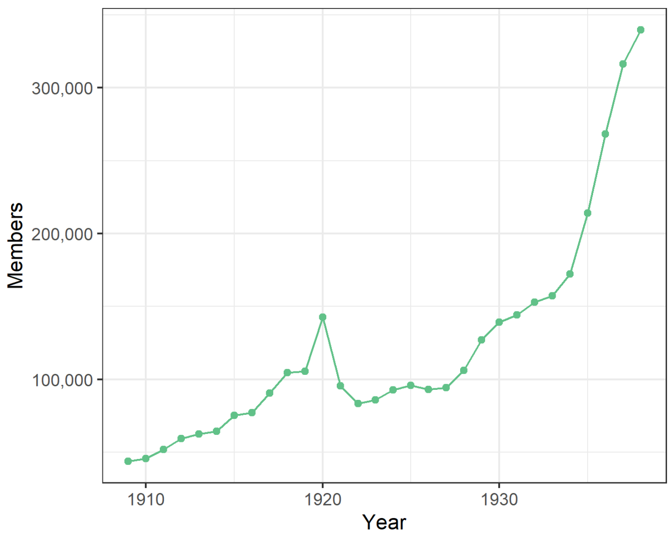


Figure A1.4: Evolution of Union Members

The figure shows the total number of members in the unions. It is clear the unions grew substantially in the period, especially in the 1930s.

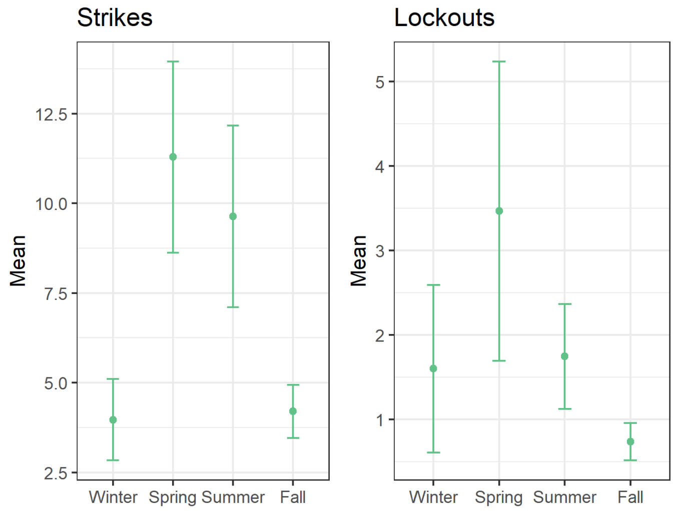


Figure A1.5: Seasonal Patterns of Industrial Conflict

The figures display the estimates of the mean number of conflicts started each season. For strikes, significantly more strikes start in the spring and the summer compared to fall and winter. The pattern is not as apparent for lockouts, but very few lockouts began in the fall. The error bars display confidence intervals on a 95 percent level.

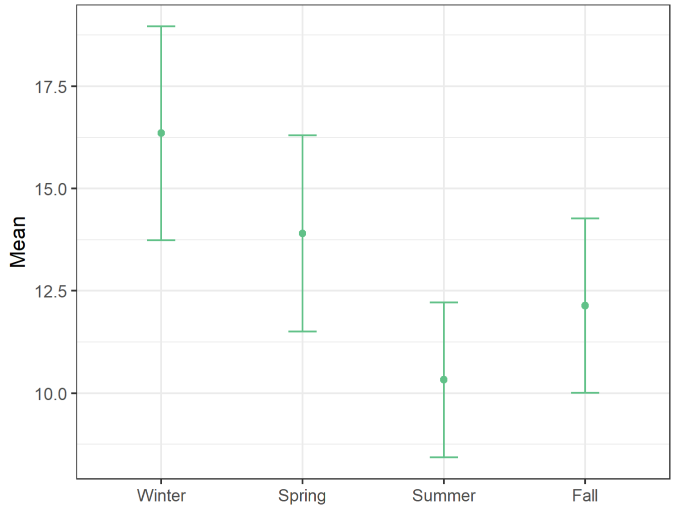


Figure A1.6: Seasonal Pattern of Unemployment

The figures display the estimates of the mean unemployment rate in the period. There is higher unemployment in the winter and spring, and lower in the summer. The error bars display confidence intervals on a 95 percent level.

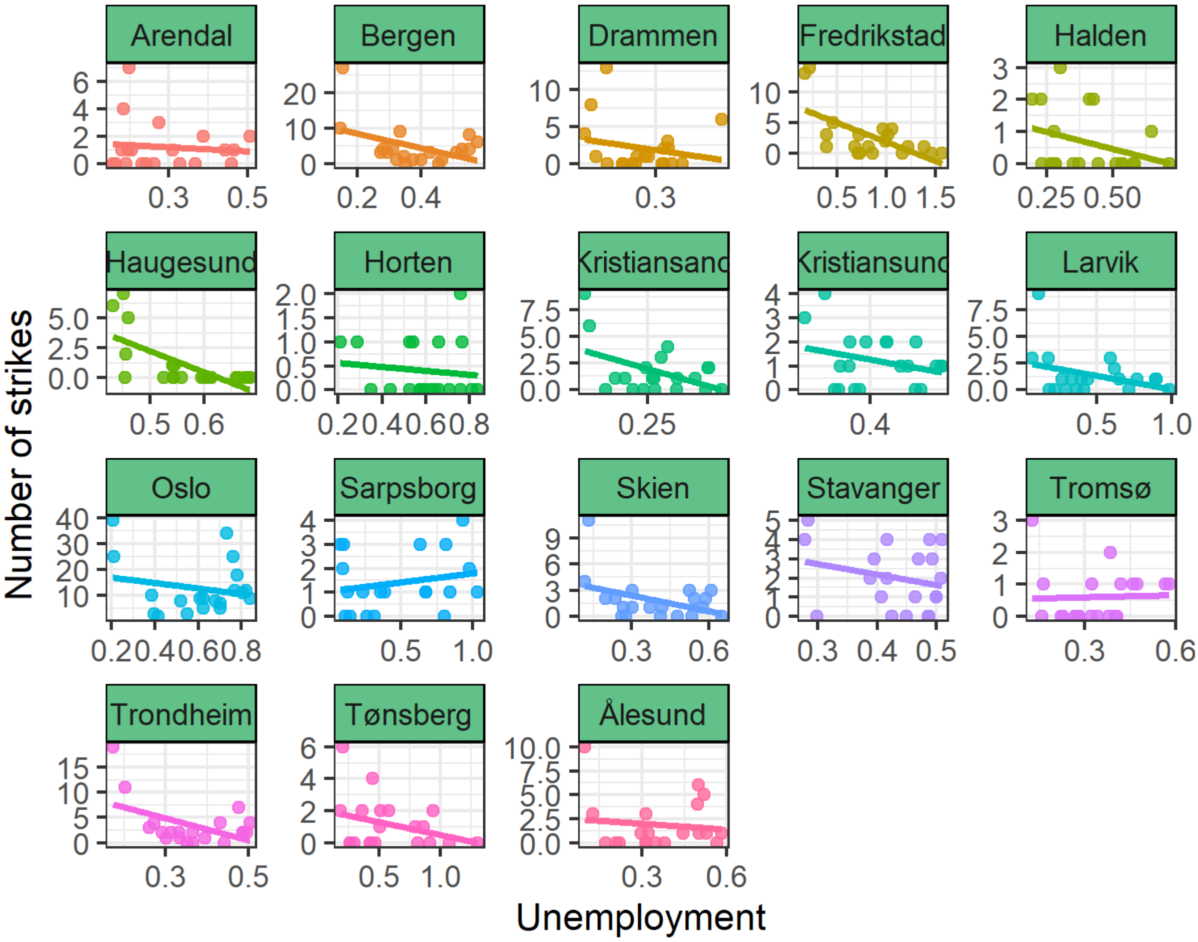


Figure A1.7: City Fixed Effects

The figure shows scatterplots of the relationship between unemployment and frequency of strikes in the 18 biggest cities. The unemployment is adjusted for the population as discussed in section 3.2. The relationship is negative for nearly all of the cities. Sarpsborg and Tromsø have a positive relationship.

Statistic	N	Mean	Median	St. Dev.	Min	Max
Strike	30	87.27	62	73.49	29	339
Lockout	30	22.63	10.5	24.61	3	100
Unemployment (SSB)	30	13.18	14.3	10.68	1	33
Unemployment (Grytten)	30	4.99	5.70	3.33	0.70	10.40
Contracts	30	731.23	445.5	838.40	98	3,820
Members	30	123,374.20	95,762	74,557.19	43,702	339,752
Labour in power	30	0.13	0	0.35	0	1
ΔWage	28	6.13	1.05	18.64	−24.55	59.44
ΔInflation	29	3.11	2.56	11.83	−16.67	40.00
ΔReal wage	28	3.07	2.05	12.57	−15.30	53.09

Table A1.1: Descriptive Statistics of the Yearly Data

The data set consists of 2618 strikes and 679 lockouts. Only a few conflicts that do not have information about starting date are lost in the merging process

Statistic	N	Mean	Median	St. Dev.	Min	Max
Strike	412	4.02	2	10.09	0	128
Lockout	412	1.07	0	2.46	0	30
Unemployment	412	9.44	7.28	9.07	0.07	47.63
Members	412	5,128.18	2,368.50	6,064.24	151.08	34,924.00

Table A1.2: Descriptive Statistics of the Data on Union Level

The data set consists of 1656 strikes and 442 lockouts. A substantial amount of conflicts are lost creating this data set. A large part of the conflicts is in other words not included in this data set. This is a result of the merging process. See section 3.3 for a discussion of this process.

Statistic	N	Mean	Median	St. Dev.	Min	Max
Strikes	360	2.35	1	4.42	0	39
Lockout	360	0.54	0	1.28	0	13
Unemployment	360	17,882.17	7,308.5	36,288.90	814	213,448
Unemployment (Population adjusted)	360	0.45	0.41	0.24	0.07	1.56
Members	342	5,029.13	1,837.50	11,667.12	163.00	94,155.00

Table A1.3: Descriptive Statistics of the Data on Geographical Level
The data set consists of 845 strikes and 195 lockouts. A substantial amount of conflicts are lost creating this data set. The main reason is that it only includes data starting in 1919. In addition, it only includes conflicts from cities and some conflicts are missing information about where the conflict took place.

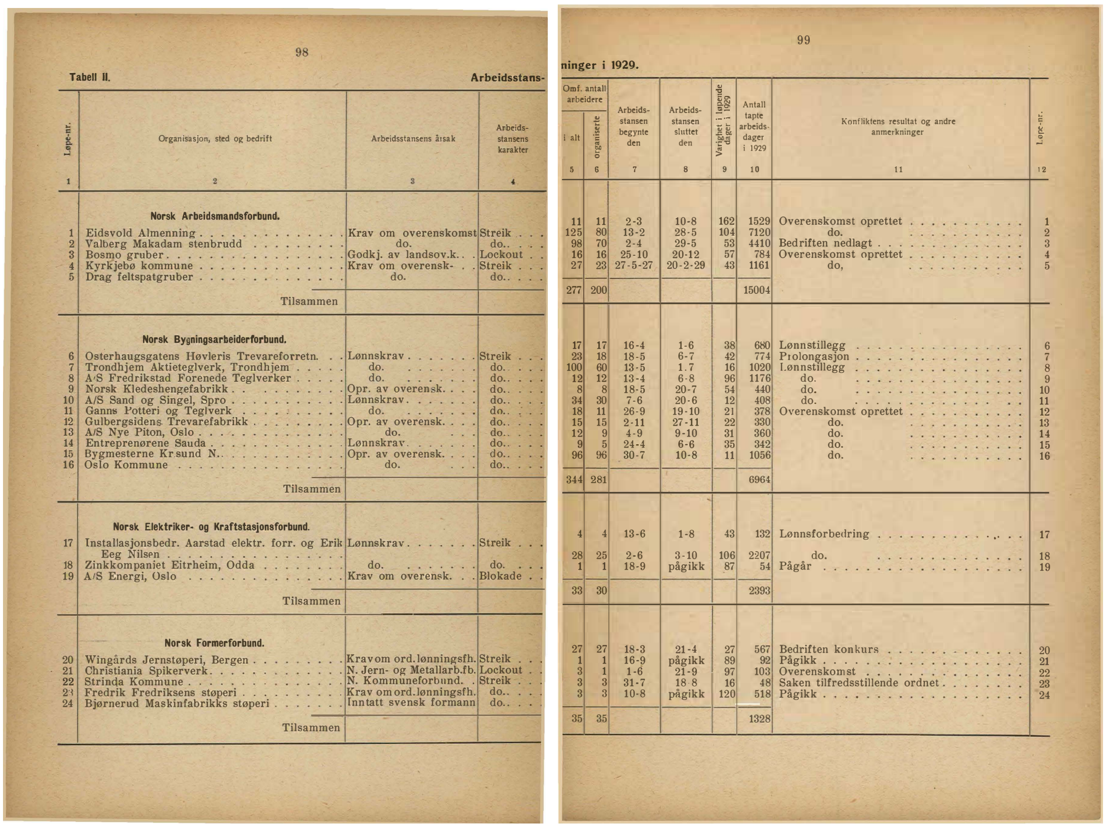
	Cause of Strike, Original	Translation	Freq	Relative_freq
1	Krav om ny overenskomst	New contract demand	541	0.204
2	Krav om overenskomst	Contract demand	381	0.143
3	Lønskrav	Wage demand	226	0.085
4	Tariffkrav	Contract demand	133	0.050
5	Lønnskrav	Wage demand	128	0.048
6	Oprettelse av overensk.	Contract demand	96	0.036
7	Krav om ny overensk.	New contract demand	92	0.035
8	Tariffrevisjon	Revised contract	79	0.030
9	Lønsreduktion	Wage reduction	62	0.023
10	Fornyelse av tariffen	New contract	58	0.022

Table A1.4: Cause of Strikes, Raw Data
The table list the ten most common causes for strikes in the data set. It lists the raw material from the data, and many of them are different versions of the same cause. It is highly dominated by contract demands.

	Cause of Lockout, Original	Translation	Freq	Relative freq
1	Overensk. ops. av arb.g.	Contract terminated	66	0.096
2	Krav om lønnsreduksj.	Demand of wage reduction	64	0.093
3	Lønsreduktion	Wage reduction	60	0.087
4	Krav om ny overenskomst	New contract demand	41	0.060
5	Lønnsreduksjon	Wage reduction	40	0.058
6	Krav om ny overensk.	New contract demand	34	0.049
7	Krav om reduksjon	Reduction demand	29	0.042
8	Trans.arb (...) ny overensk.	New contract transp.workers	28	0.041
	Krav om overholdelse	Compliance demand		
9	Bygningskonflikten	Construction conflict	21	0.030
10	Krav om overenskomst	Contract demand	21	0.030

Table A1.5: Cause of Lockouts, Raw Data

The table lists the ten most common causes for lockouts in the data set. The list has some similarities to the one for strikes, however, wage reduction and contract termination are an important part of this list.



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Tabell II. Arbeidsstansninger i 1929.

Løpe-nr.	Organisasjon, sted og bedrift	Arbeidsstansens årsak	Arbeidsstansens karakter	Omf. antall arbeidere: i alt	Omf. antall arbeidere: organiserte	Arbeidsstansen begynte den	Arbeidsstansen sluttet den	Varighet i løpende dager i 1929	Antall tapte arbeidsdager i 1929	Konfliktens resultat og andre anmerkninger	Løpe-nr.
1	2	3	4	5	6	7	8	9	10	11	12
	Norsk Arbeidsmandsforbund.										
1	Eidsvold Almenning	Krav om overenskomst	Streik	11	11	2-3	10-8	162	1529	Overenskomst oprettet	1
2	Valberg Makadam stenbrudd	do.	do.	125	80	13-2	28-5	104	7120	do.	2
3	Bosmo gruber	Godkj. av landsov.k.	Lockout	98	70	2-4	29-5	53	4410	Bedriften nedlagt	3
4	Kyrkjebø kommune	Krav om overensk-	Streik	16	16	25-10	20-12	57	784	Overenskomst oprettet	4
5	Drag feltspatgruber	do.	do.	27	23	27-5-27	20-2-29	43	1161	do,	5
	Tilsammen			277	200				15004		
	Norsk Bygningsarbeiderforbund.										
6	Osterhaugsgatens Høvleris Trevareforretn.	Lønnskrav	Streik	17	17	16-4	1-6	38	680	Lønnstillegg	6
7	Trondhjem Aktieteglverk, Trondhjem	do.	do.	23	18	18-5	6-7	42	774	Prolongasjon	7
8	A/S Fredrikstad Forenede Teglverker	do.	do.	100	60	13-5	1.7	16	1020	Lønnstillegg	8
9	Norsk Kledeshengefabrikk	Opr. av overensk.	do.	12	12	13-4	6-8	96	1176	do.	9
10	A/S Sand og Singel, Spro	Lønnskrav	do.	8	8	18-5	20-7	54	440	do.	10
11	Ganns Potteri og Teglverk	do.	do.	34	30	7-6	20-6	12	408	do.	11
12	Gulbergsidens Trevarefabrikk	Opr. av overensk.	do.	18	11	26-9	19-10	21	378	Overenskomst oprettet	12
13	A/S Nye Piton, Oslo	do.	do.	15	15	2-11	27-11	22	330	do.	13
14	Entreprenørene Sauda	Lønnskrav	do.	12	9	4-9	9-10	31	360	do.	14
15	Bygmesterne Kr.sund N.	Opr. av overensk.	do.	9	5	24-4	6-6	35	342	do.	15
16	Oslo Kommune	do.	do.	96	96	30-7	10-8	11	1056	do.	16
	Tilsammen			344	281				6964		
	Norsk Elektriker- og Kraftstasjonsforbund.										
17	Installasjonsbedr. Aarstad elektr. forr. og Erik Eeg Nilsen	Lønnskrav	Streik	4	4	13-6	1-8	43	132	Lønnsforbedring	17
18	Zinkkompaniet Eitrheim, Odda	do.	do.	28	25	2-6	3-10	106	2207	do.	18
19	A/S Energi, Oslo	Krav om overensk.	Blokade	1	1	18-9	pågikk	87	54	Pågår	19
	Tilsammen			33	30				2393		
	Norsk Formerforbund.										
20	Wingårds Jernstøperi, Bergen	Kravom ord.lønningsfh.	Streik	27	27	18-3	21-4	27	567	Bedriften konkurs	20
21	Christiania Spikerverk	N. Jern- og Metallarb.fb.	Lockout	1	1	16-9	pågikk	89	92	Pågikk	21
22	Strinda Kommune	N. Kommuneforbund.	Streik	3	1	1-6	21-9	97	103	Overenskomst	22
23	Fredrik Fredriksens støperi	Krav om ord.lønningsfh.	do.	3	3	31-7	18 8	16	48	Saken tilfredsstillende ordnet	23
24	Bjørnerud Maskinfabrikks støperi	Inntatt svensk formann	do.	3	3	10-8	pågikk	120	518	Pågikk	24
	Tilsammen			35	35				1328		

Figure A1.8: Example of Raw Data

Example of the tables used to create the data set about industrial conflict. This is from 1929.