

# **Productivity and Maternity Leave – Findings from a Norwegian Insurance Company**

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**Master's Thesis**

This master's thesis is submitted for completion of the following degree:

**Master of Economics**

The University of Bergen, Department of Economics

December 2013

UNIVERSITETET I BERGEN



## Acknowledgements

This paper marks the end of my fifth and final year as a student of economics and political science. I wish to thank the University of Bergen, the University of Oslo and Université Paris Dauphine. Not only have these institutions provided me with the attitudes, skills, and knowledge to make something of myself, they have also been an arena of personal development and an important part of my life. I would especially like to thank my guidance professor Arild Aakvik for great help in the process with this paper. He has always been available, and ready to help, when my frustrations are high or when I need a sparring partner. I would also like to thank my friends in the English language studies: Hanne Frafjord, Ingrid Rivedal Yndestad, Mari Mulelid, Armin Zahirovic and Kristoffer Humphrey for valuable feedback on language. I want to thank my fellow students Tom Meling, Marte Lunde Tobro and Signe Abrahamsen for important feedback on my paper. Lastly I would like to thank all my friends, and especially Bruna Dias, for having to endure my frustrations and yet always supporting me and giving me the needed reserves to fulfill this task.

I dedicate this paper to my parents, Irene and Geir Tore Saakvitne, without whom nothing of this would have been possible.

*Tor Gunnar Saakvitne*

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Tor Gunnar Saakvitne, Bergen 1<sup>st</sup> of December 2013

## Abstract

### **Productivity and Maternity Leave – Findings from a Norwegian Insurance Company**

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The University of Bergen, 2013

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This paper explores the relationship between maternity leave and productivity. It explains and discusses the different applications of such a benefit, and discusses the change in this institution over time in Norway. It also presents the costs such a system is imposing on the governmental budgets. Furthermore, it reviews previous literature on the effects from maternity leave and absenteeism on health, the labor market, and productivity. The research is empirical and analyzes weekly data on individuals working in an insurance company based in Norway for the time period of 2003-2009; the data is thus a panel. It analyses the data with the fixed effects approach and by using the difference-in-difference method (DID). It also controls for problems which may occur in DID estimation such as autocorrelation, heteroskedasticity and potential outliers. The estimation controls for both linear individual-specific trends and quadratic individual-specific trends. This paper then finds, on average, a negative effect from maternity leave on productivity. This negative relationship is found to be largely caused by the first 0-20 weeks of returning from such a leave. In addition maternity leave seems to have similar effects on average as a period of 10 weeks absence for other reasons from work. The findings suggests that since the 0-20 first weeks are the main cause of the negative effect on productivity, other factors such as getting reaccustomed to work might be the main reason for the drop in productivity. In addition it argues that without maternity leave the negative effects from giving birth on productivity might have been worse. The statistical program STATA is used for analyzing the data.

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# 1 Introduction

## 1.1 Background

This paper seeks to investigate the effect of maternity leave on productivity. It is thus an effect evaluation and compares the before and after averages between groups over time. The individuals are placed in either the treatment or the comparison group based on some assumed exogenous event (here giving birth). It uses a panel data where we have weekly observations for 256 women between 2003 and 2009.

Previous research on the subject of pregnancy and maternity leave in economics has mostly focused on how wages, labor supply, and the retention rate can be expected to respond to market imperfections such as maternity leave. Ruhm (1998) classifies maternity leave as a market imperfection leading companies to set lower wages to compensate for the absence of the worker. However, when looking at maternity leave, theorists have largely been focused on voluntary maternity leave schemes. They have not focused extensively on governmental programs where companies are obliged to provide an opportunity for paid maternity leave. The companies are then compensated for most of the wage costs by the government. When the government are the institution that are bearing the largest financial burdens in such a system the market failure can be alleviated, as Ruhm (1998) also suggests, to a certain degree.

But what of the other costs such a system inflicts on the economy? There are for instance certainly distortion costs for companies when they are forced to hire substitutes. They need training and adjustment to the specific tasks they shall provide in the companies. Another issue which arises, and which have been asked by several researchers such as Ruhm (1998), Rønsen & Sundström (1996) and Lai & Masters (2005) is; what happens to the workers' human capital when it is absent from work for such a long period? This is exactly what we will try to answer. We will observe what productivity reactions maternity leave produce for our workers. In essence we are seeking to observe how human capital is affected by such a leave and how this can influence the productivity patterns of individuals.

Authors such as Markussen (2012) finds evidence that sick leave causes wages to fall, and if wages are a true reflection of workers marginal productivity, this should lead us to conclude that this kind of absence causes lower productivity. The question we thus need to ask ourselves is if maternity leave is a different kind of leave, not as prone to screening and signaling effects as with sick leave, and not with the same potential to be determined



endogenously. On the one hand it is absence from work, and absence from work can hardly be suspected to be good for productivity unless it is assumed that the individuals draws motivation from not working, or draws an intrinsic motivation from being able to combine work and family more efficiently. On the other hand, maternity leave is not a normal absence from work, but an absence caused by presumed exogenous factors and a life changing event which are likely to stir up unexpected reactions.

The data is a panel; we have weekly observations on 256 women for a total of 332 weeks from the time period 2003-2009. The data is unbalanced, which means we will have less observations for some individuals than for others. This is because some of the workers are not working in this company, or this specific department, for the entire time period. The data is collected from the Norwegian branch of an international insurance company. The individuals observed works in the call center department and are tasked with selling insurance products as well as providing customer services. They work in teams. We have access to the minutes logged on to their sales system per week, number of sales per week, number of telephones answered per week, and the value of sales per week. We also have dates specifying when the individuals gave birth as well as registrations of absence for reasons such as sick leave and vacations.

The paper uses the fixed effects approach, and more specifically the difference-in-differences methodology, for evaluating the effect from maternity leave on productivity. It has several different estimation strategies. First it analyses the effect when the fixed effects are constant, and not allowed to trend over time. Secondly it includes individual-specific linear trends to allow for slow moving trends for the unobservables. Thirdly it includes an additional individual-specific quadratic trend to allow for a more complex dynamic behavior in the unobservables. It also analyses how maternity leave affects productivity over time. In addition the paper compares the effects from maternity leave on productivity to the effects from general absence on productivity. Finally it controls for different potential problems such as autocorrelation, heteroskedasticity, and potential outliers.

The paper finds a negative effect from maternity leave upon productivity. This effect is then found to be largest and most significant in the first 0-20 weeks upon return. The results are to a large degree robust to both problems of heteroskedasticity and autocorrelation. However, when controlling for autocorrelation the results become less significant when adding individual-specific quadratic trends. The results from the estimations are robust to problems

of potential outliers. The negative effect from maternity leave is also similar to the effect from an absence of 10 weeks. It is speculated that, since the negative effects from maternity leave is largest and most significant during the first weeks after returning, the effects can be attributed to a period of “relearning” the job as opposed to a detrimental effect from the period of maternity leave itself.

### **1.2 Structure**

The structure of the paper is as follows; Chapter 2 presents the institutional factors and laws which regulate the maternity leave scheme; it also includes a historic view on maternity leave and women’s participation in the labor force in Norway, a comparison to maternity leave in other nations and a general overview of the costs such a system imposes. Chapter 3 lists and discusses the relevance of previous findings of the economic, physical, and psychological effects from absenteeism and maternity leave on productivity. It also discusses briefly the “double burden” hypothesis often researched in sociology and other fields. Chapter 4 presents the data, the company we are observing, adjustments made to the data, and the limitations of our own dataset. Chapter 5 discusses the difference-in-difference methodology which is used to identify the effect from maternity leave on productivity. Chapter 6 then presents the results, different specifications to the models, sensitivity analysis, and a comparison of the main results. Chapter 7 concludes the paper and discusses the relevance, variability and reliability of our results as well as suggestions for further research.

## 2 Institutional Factors

Before we introduce the previous research made on maternity leave we need to discuss the institutional factors of maternity leave in a Norwegian perspective. To be able to discuss maternity leave as a governmental scheme we must see what the reasons are and what the logic is behind such a system, who administers it, and what it costs. We also need to compare the Norwegian system to other systems for maternity leave around the world. It is essential also when discussing such a scheme to take a look at women's history in the labor market. A major shift has occurred in the last 50 years from women being primarily housewives and homemakers, towards taking part in the paid labor market in the same way as men. We will start off by taking a look at the history of women's introduction to the labor market and continue with discussing the maternity leave today and its historical development as a governmental scheme. In the end we discuss the Norwegian maternity leave in a global perspective and the costs of maternity leave.

### 2.1 Background on Women's Participation in the Norwegian Workforce

The number of women employed in Norway has been steadily increasing over the last 40 years. From 1972 to 2010 the numbers went from approximately 600 000 women employed to around 1 200 000 (Koren, 2012). According to Koren (2012) this increase of 600 000 women is equivalent to the number of housewives disappearing from the statistics in that same period. This is both because the older generation of housewives disappeared, and because the new generation never became housewives. More women are working fulltime, as well as part-time jobs, and are by now fully integrated in the Norwegian labor market. In 1972, 40% of the women between the ages of 16-74 considered themselves primarily housewives. 60% of these 40% were married women. In comparison, in 2009, these shares were respectively 3% and 6% (Koren, 2012: 24). According to Koren (2012) many of the women that emigrated to paid labor went into work that resembled what they used to do at home, like for instance childcare, cleaning, canteen-work, and nursing of the elderly and the sick.

The massive reorganization of everyday life is proof of the massive reorganizing of women's roles in society. Children are now guaranteed by law a spot in the kindergartens in Norway, and the sick and the elderly are living under the care of the public health care system. A reason for this is the general income growth in Norway starting in the 1970's. Thus the government was more prone to supporting the transition from the private to the public sphere

of traditional tasks attributed to women (Koren, 2012). This made it easier for women to enter the labor market and contribute at the same level as men.

In 2012, 417 022 women worked in health and social services compared to 93 707 men in the same sector, while in industrial work the figures were 175 217 men and 53 975 women (SSB, 2013a). This example indicates that there is still gender differences present in the labor market. A concern for us is the potential inequality in the distribution of work also at home, making the workload larger for women. In this case there might be implications on productivity at work because women are working more than men in total. If the workload is too high, this might cause fatigue or stress which could affect productivity. Such a potential “double burden” is discussed further in section 3.6 below.

### **2.2 Maternity Leave Today and the Responsible Authorities**

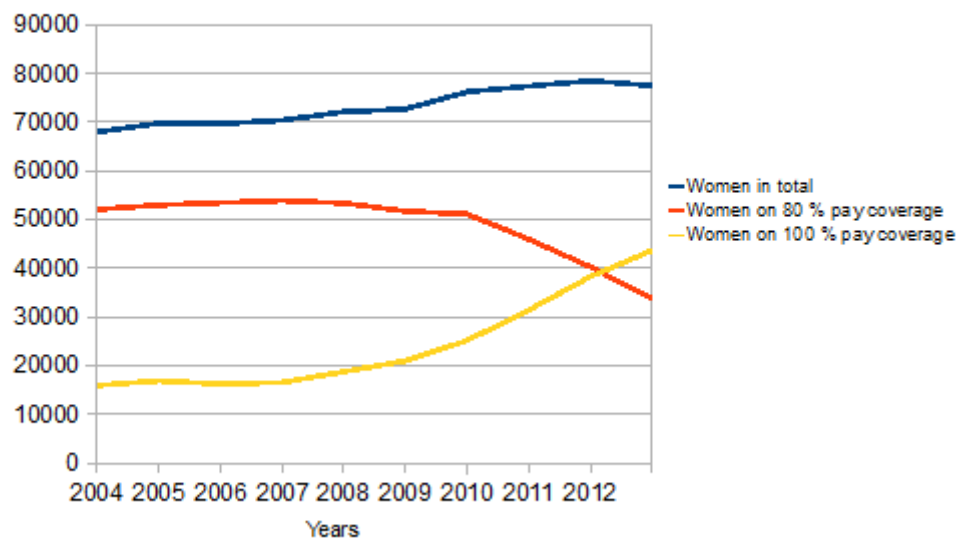
In Norway the responsible authorities for maternity leave is the Norwegian Labor and Welfare Administration (NAV).<sup>1</sup> When applying for maternity leave you apply directly to the NAV. The wages are then covered by the governmental “Folketrygd” – a governmental insurance system based mainly on income from taxes. Hence, this is mainly a cost that falls on the governmental budget and not the specific company budget.<sup>2</sup> The main costs for the companies are the distortion costs from replacing the absent employee, although these costs might be great. In our observation period parents could choose from leaving work for 42 weeks with 100% wage-coverage, or leaving for 52 weeks with 80% wage-coverage, as well as minor different applications.<sup>3</sup> Below we see a diagram depicting the development in the usage of maternity benefits for women in the period between 2003 and 2012 (NAV, 2013a).

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<sup>1</sup> NAV are also responsible for other benefits such as sickness benefits, family and pension services, occupational rehabilitation, and financial social help.

<sup>2</sup> The government does not cover wages above 6G; we explain this more in section 2.3.

<sup>3</sup> More about these different applications in section 2.3.

**Figure 1: Women in Norway Receiving Maternity Benefits, 2003-2012**

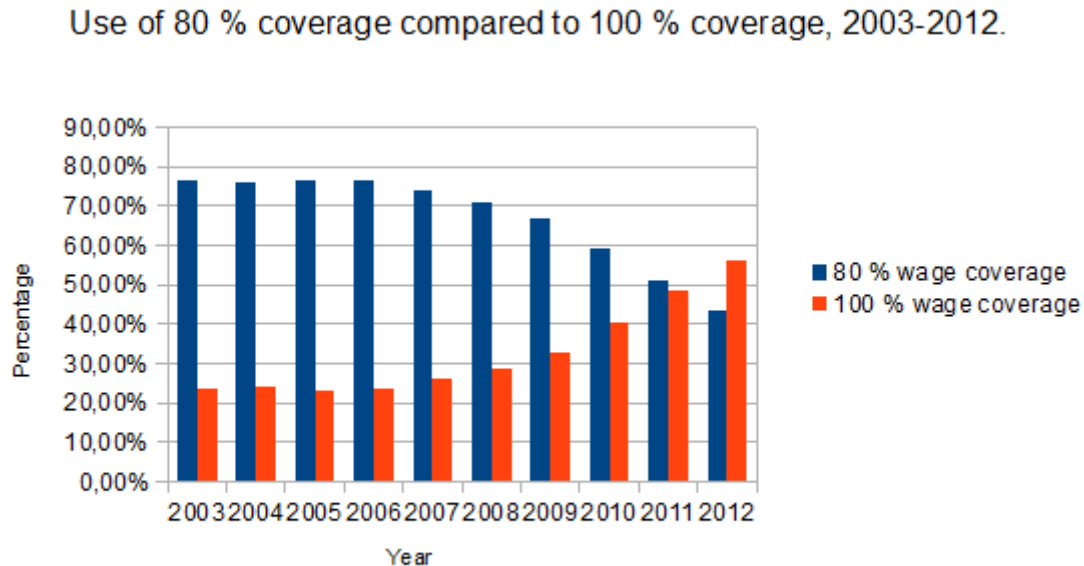
*Note: Number of women on y-axis. Source: NAV (2013a)*

What is interesting is that, in the period 2004-2007, it seems that most women used the right to have 52 weeks with 80% coverage compared to the 100% coverage for 42 weeks. However, from 2007, we see an increase in the use of 100% coverage and a decrease in the usage of 80% coverage. There are several explanations for this. One of them is that the government pledged to have full childcare coverage by 2008. Subsidizing prices for childcare has made it more available for everyone, independently of family income. Hence it is plausible that more women are using the right to have 42 weeks with 100% coverage because it is easier to find childcare, the mother no longer needs to stay at home with the child for a full year. Another reason for this is pure economics. If a woman earns 450 000 NOK each year this amounts to a weekly wage of 8654 NOK. 100% of this for 42 weeks equals 363 461 NOK, while 80% of 8654 NOK for 52 weeks amounts to slightly less than 360 000 NOK. So we see that it is more profitable for a woman to choose 100% coverage for 42 weeks.<sup>4</sup> The change from the usage of 80% to 100% occurred while women using the maternity leave in total increased. A reason for the increase in the usage of maternity leave as a whole could be that there has been a 7.12% increase of women between the ages of 16-44 in this period (SSB, 2013b). This increase of women in childbearing age can be expected to cause an increase in

<sup>4</sup> For the new system where women are given 49 weeks of 100% wage coverage and 59 weeks of 80% coverage (introduced in July 2013) it is shown that the differences are even greater (above 10 000 NOK). See for instance Moflag (2012) for more on this.

the total amount of women using maternity leave benefits. To further illustrate this rather dramatic change from 80% to 100%, we may observe the changes in percentages.

**Figure 2: Application of Different Maternity Benefits Schemes**




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*Source: NAV (2013a).*

The importance of this rather dramatic shift from 80% coverage for 52 weeks towards 100% coverage for 42 weeks is that women will be away from the workplace on average for shorter periods than before; the period of absenteeism is hence reduced. This might be positive from a productivity view if one assumes that absenteeism influences productivity. Another importance is that we have two different applications of the maternity leave scheme. This might give some different results when analyzing the effects of maternity leave on productivity. We do not have information on whether the observations in our data are gathered from women using the 80% coverage or the 100% coverage. Hence, it is difficult for us to separate the two and analyze them separately. This change is rather interesting and should perhaps be the focus of future research, but will not be studied more here.

### 2.3 The Historical Development of Maternity Leave in Norway

Maternity leave was introduced in Norway already in 1909 along with the introduction of sickness benefits for workers, women was then paid for 6 weeks after the birth of their child for staying at home (Barne-, Likestillings- og Inkluderingsdepartementet, 1996). This was mostly used by unmarried women since they were the ones working at that time. From 1915

married women were also given a onetime payout of 40 NOK under the requirement that the husband was insured against sickness (Barne-, Likestillings- og Inkluderingsdepartementet, 1996).

The modern maternity leave benefits were first introduced in 1946, along with other family oriented benefits such as the “Barnetrygd” - financial support for children (Skevik, 2005: 219-220). In 1946 it was limited to 12 weeks, the mothers were given support the same way as sickness pay which in 1946 was less than full compensation of the their wages (Skevik, 2005: 219-220). In 1977, after several demands from the women`s movement (Koren, 1997), the maternity leave period were expanded from 12 to 18 weeks and increased to include 100% coverage of the women`s wage. It was in addition introduced by law that 12 of the total of 18 weeks could be distributed among men and women as they themselves saw fit (Skevik, 2005: 219-220). The next increase in allocated time for maternity leave occurred in 1988, when maternity leave were increased to 22 weeks. From this point on the period of maternity leave were increased several times during the 1980`s and early 1990`s until in 1993 it was at 42 weeks with full wage compensation and 52 weeks with 80% coverage (Skevik, 2005: 219-220). In 1993 it was also decided that 3 of these weeks had to be used pre-birth and 6 weeks post-birth for women (Barne-, Likestillings- og Inkluderingsdepartementet, 1996).

During our observation period, the law was that the parents in total could use 42 weeks of maternity leave with full wage compensation or 52 weeks with 80% wage compensation in accordance with the changes that were implemented in 1993. The fact that both parents might use some of these benefits renders the term maternity leave a bit futile in a Norwegian perspective. However, it is still skewed towards women being the main benefactor with 9 weeks reserved for the mother and 4 weeks reserved for the father (Skevik, 2005: 219-220). Women are also the main user of the leave.<sup>5</sup> Lately there have also been some changes, and as of the 1<sup>st</sup> of July 2013 it is currently at 49 weeks with full wage compensation or 59 weeks with 80 % compensation – with 14 weeks allocated to each parent, and 18 weeks to allocate among themselves (NAVb, 2013).<sup>6</sup> The recent developments are not relevant for us because our observation period ends in 2009, although they might indeed have a large impact on the labor market in the future. It is worth pointing out that 29 of the weeks in the case of 100% coverage, and 39 of the weeks with 80% coverage, may be shared between the parents as they

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<sup>5</sup> See section 2.4.

<sup>6</sup> 28 weeks with 80 % coverage to allocate among themselves.

themselves see fit by the valid rules in our observation period.<sup>7</sup> This creates potential problems for our analysis since we have no formal indication of when a period of maternity leave starts and when it finishes, only a date specifying the birth of the child. Thus we have no means of rendering how the parents allocate the weeks between them, and which application in terms of weeks they chose. But as we shall see below, women are the main user of these benefits; so the problem might not be as decisive.

Furthermore, there are also other laws regarding maternity leave. The parent must have been in the current job for a minimum of 6 out of 10 months before the maternity leave to be eligible for leave with pay (Skevik, 2005: 219-220). Also, to be eligible for the maternity leave you must have earned an amount corresponding to a minimum of half of the basic amount in the “Folketrygd” (Nordseth & Sivertstøl, 2006).<sup>8</sup> The 100% coverage is valid up to and including 6G for employees, and 65% of presumed income up to and including 6G for individuals with their own company (Nordseth & Sivertstøl, 2006). This means that potentially companies will have to compensate for wages above this level if the worker are absent due to maternity leave.<sup>9</sup> There are also some other specifics, such as the parents may use the leave as a reduced work percentage during the period and they can thereby stretch the period of leave out over a longer time period (Skevik, 2005: 219-220).<sup>10</sup> If the mother did not have the necessary tenure within the workplace, she would be eligible for a one-time payout. If the mother received this, the father could take out 39 weeks with 80% coverage or 29 weeks of 100% coverage on the condition that the mother will start working again, study, or be on sick leave after the birth (Skevik, 2005: 219-220). As long as the children are under the age of 12, the parents can also stay at home for a total of 10 days each parent per year if they have a sick child (Skevik, 2005: 219-220).

The maternity leave schemes in Norway have been built on equality arguments. Since only 9 weeks are reserved exclusively for the mothers, it provides the women with incentives to be able to quickly and efficiently return to their workplace, although most women use the time allocated to them. The fact that Norway also has a quota reserved for the fathers give men incentives to be able to participate actively in the initial care of their children, which is presumed to increase equality also at home. However, there is some discussion about whether

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<sup>7</sup> 9 weeks allocated to the mother, 4 weeks allocated to the father.

<sup>8</sup> The equivalent of 1G by Norwegian standards.

<sup>9</sup> Whether or not the employer wants to compensate for wages above 6G is up to the respective employer.

<sup>10</sup> The minimum percentage is 50% and is to be stretched over no longer than 2 years.



these laws have the wanted effect. This is because women are still seen as the primary caretaker of children. Research also shows that women are more often the ones with the primary care of the household (Halrynjo, 2009).

The complexity of these schemes makes it hard to root out a clear effect from the marginal amount of time that women are on maternity leave. We can only observe maternity leave as it is with different amounts of weeks away from work per women, and then see if the time away from work affects productivity. A woman might for example be absent for 52 weeks with 80% coverage or 42 weeks with 100% coverage, we also have to bear in mind that 4 of these weeks are reserved for the father in the observation period. If the father used these 4 weeks, the mother would be absent from work for an even shorter period. It is therefore necessary for us to make the rather strong assumption that the different applications of maternity leave will not have a significant effect on their performance when they return. However, this assumption is perhaps not as strong when looking at how the system is applied in reality.<sup>11</sup> We therefore analyze maternity leave as a whole, while making some assumptions on the applications of maternity leave which shall be discussed further below.

It is worth noting that during the 1930's in Norway, it was a goal in itself to keep women away from paid labor (Sørskår, 1988). This changed in the 1960's and 1970's when the labor market was in need of women to keep up the labor supply. In addition more women entered the labor force and there was therefore a demand for such arrangements. In fact, the economic situation of Norway in the 1970's was used as an argument to not expand the maternity leave period (Sørskår, 1988). A proposal to increase the maternity leave period to 18 weeks was voted upon in 1970, but was not passed (Barne-, Likestillings- og Inkluderingsdepartementet, 1996). The proponents were arguing that married women's participation in the workforce were expected to increase, thus it would be important for society to make it possible to combine work and the care of children (Barne-, Likestillings- og Inkluderingsdepartementet, 1996). The opponents argued that although there was a need to prolong the period of

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<sup>11</sup> Below we will present some studies claiming that time away from work equals depreciation of human capital, and loss of appreciation of human capital (Rønsen & Sørensen 1996, Ruhm 1996). Under this assumption we might expect that for example taking out 52 weeks with an 80 % wage compensation would lead to a greater productivity loss than taking out the 42 weeks with 100 % compensation. However, this effect is likely to be small in reality. This late in the leave period, the expected depreciation of human capital should be expected to have occurred already, and an extra time away off 10 weeks should not make a large difference in the overall picture. According to Statistics Norway, very few women are using the alternative of working part time over a longer time period than 52 weeks (Danielsen & Lappegård, 2003); we will therefore not consider this alternative in greater detail in the rest of the paper (in 2002 only 2.2% of the women receiving maternity leave benefits used this arrangement).

maternity leave, the economic consequences of this needed to be studied (Barne-, Likestillings- og Inkluderingsdepartementet, 1996). On the basis of this request, the Norwegian Equality Council suggested to raise the period of maternity leave from 12 to 18 weeks in 1973 (Kommunal- og Arbeidsdepartementet, 1975-1976).<sup>12</sup>

The pressure from the women's movement (Koren, 1997), and advices from the Norwegian Equality Council, eventually led to the largest change both ideologically (with the change from perceiving women as homemakers towards a source of labor supply) and institutionally (by expanding the period with 6 weeks and increasing the coverage to 100% of the wage) in 1977. It is possible that the sudden source of income from oil had an influence on the economic arguments at the time, rendering the needs of women more important than the financial burden such a system would have on the governmental budgets. Sørskår (1988) argues that while in Sweden maternity leave was used as a tool to get more women to work, in Norway it was rather a consequence of more women working. An important reason for the change in 1977 was the Norwegian Labor Party arguments that it would improve women's health (Sørskår, 1988). According to Sørskår (1988) this has been the general argument every time a change to the maternity leave system has been debated in Norway. After this change in 1977 the maternity leave period has been further expanded throughout the years, and is at this moment at a comparatively high level.

Today the debate about maternity leave as a system is not fierce in Norway, and the consensus that this is a system we need is highly present. It is most often legitimized based on equality arguments, and the ability it gives women to combine work and family life without considerable loss of income (Skevik, 2005). The quota allocated for fathers is more controversial as it is perceived to reduce the family's freedom of choice. The new government in Norway has proposed a drop in the weeks allocated to the father from 14 to 10 weeks, and introduced several opportunities for exceptions from using these 10 weeks (Statsministerens Kontor, 2013). Equality arguments along with the need for fathers to bond with their infants are the arguments presented for this quota (Skevik, 2005). The arguments are hence more about how families should allocate the maternity leave among its members rather than the economic consequences or legitimacy of the system. Skevik (2005) argues that because the

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<sup>12</sup> "Likestillingsrådet", which is now restructured and its successor is the "Likestillings- og diskrimineringsombud" ("The Equality and Anti-Discrimination Ombud").

amount received during maternity leave is highly dependent on previous income, it can be argued that income distributive arguments are not given much weight in this matter.

### 2.4 Comparison to Similar States

It is useful to see how the maternity leave is organized in some similar and comparable states for illustration. According to the Swedish government (Försäkringskassan, 2013), Sweden has a total maternity leave period of 16 months with 80% pay coverage. The parents can share these months between them, except for 2 months which has to be used by each parent. Iceland has divided its maternity leave period into three. 3 months are allocated to each parent while the remaining 3 months are to be divided between the parents as they themselves see fit (Barne-, Likestillings- og Inkluderingsdepartementet, 2010). Denmark does not have a specific quota for fathers, and the general picture is that women use the greater part of this leave (Barne-, Likestillings- og Inkluderingsdepartementet, 2010). Thus, compared to many of our neighboring states Norway has a relatively generous maternity leave scheme.

Norway's maternity leave scheme is very generous compared to the major nations of the world. In comparison the U.S. has only 12 weeks of unpaid maternity leave (The Family and Medical Leave Act, 1993). The UK currently has 39 weeks of paid leave, although not with 100% coverage for the entire time period (Local Government Employers, 2013), France has 16 weeks of full pay with an extra 10 weeks for the 3<sup>rd</sup> child (l'Assurance Maladie, 2013).

According to the Norwegian government, the trends in Scandinavia are that women are using most of the leave that can be allocated between the parents (Barne-, Likestillings- og Inkluderingsdepartementet, 2010). It is reported that in 2009, Danish fathers used 7% of the total amount of the maternity leave period, Norwegian fathers used 12%, Icelandic fathers used 34%, and Swedish fathers used 23%.<sup>13</sup> This accentuates the fact that it is mostly women using maternity leave. Hence it is useful to look at women in our sample and leave out men from the equation. But as the percentage of men using maternity leave increases it would be interesting to look at men as well and see how they are affected by such a period of absenteeism from work.

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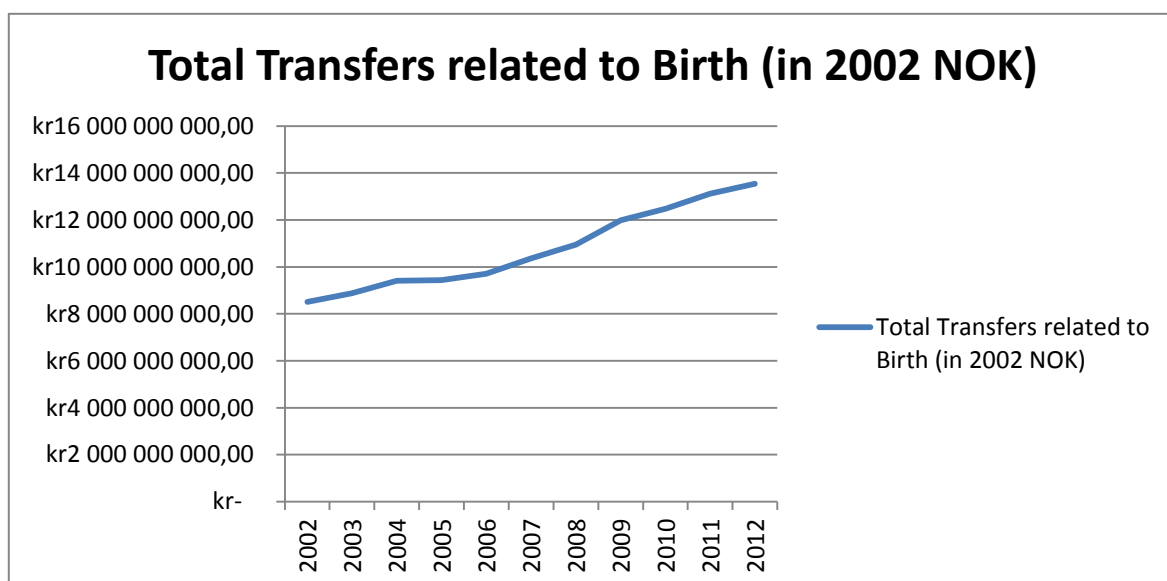
<sup>13</sup> The high values for Icelandic fathers are due to its 1/3 division of the maternity leave.

## 2.5 Total Governmental Spending in the Area of Interest

The Norwegian government spends a high percentage of GDP on public social expenditures each year. According to the OECD (2013), Norway spends 23.3% of their GDP on public social expenditures. The OECD average is 22.1%. Norway's GDP per capita is estimated at approximately 98 664 USD in 2011 (IMF, 2013). Spending 23.3% of the GDP on social expenditures thus amounts to approximately 23 000 USD each year per capita. Hence while Norway might not be spending much more than other countries in percentages, because of our high GDP per capita the government is spending a larger amount than many other countries on social expenditures. We will observe below what the Norwegian government reports about their spending on maternity benefits.

These statistics are gathered from the report the Norwegian Department of Finance presents each year to the legislative assembly (Finansdepartementet, 2002-2012b).<sup>14</sup> The data depicts the development in total transfers from the governmental budgets to compensate companies for wages related to maternity leave benefits over the time period 2002-2012 in Norway.

**Figure 3: Development of Monetary Transfers for Birth-Related Expenses in Norway**



*Note: The monetary amounts are adjusted to the CPI where 2002 is the basis year (2002=100). Source: Finansdepartementet (2002-2012b).*

<sup>14</sup> The data is collected from St.Meld.3 (Statsregnskapet) from each year between 2002 and 2012. This report by the Norwegian Department of Finance is presented each year to the legislative assembly ("Stortinget"). The post is 2530: "Stønad ved fødsel og adopsjon", or "Monetary Transfers Associated with Birth and adoption". This includes a one-time payout associated with birth and adoption, compensation for wage during maternity leave, and compensation for "feriepenger" or "holiday money".

We observe an increase in birth-related expenses. This increase is likely to be caused mainly by the increase in women that are receiving maternity benefits (see *Figure 1*). It might also be caused by the expansion of maternity leave benefits to include men to a higher degree. Men have on average higher income than women; hence governmental transfers could increase if more men take advantage of the maternity leave benefits. In addition, the real wages has increased in Norway since 2002; this naturally causes the compensation to the companies for wages during maternity leave to increase.<sup>15</sup> According to Statistics Norway (SSB, 2013c), the Norwegian GDP in 2012 was 2565 billion NOK. Hence, looking at the figure above, the costs towards maternity leave were in 2012 approximately 0.5% of the GDP.

This is not necessarily a large figure from a direct cost perspective. However, if the potential indirect effects from this are included, the costs can be expected to be even higher. Such an indirect cost might for instance be that the employers lose valuable workers at critical times, they may have to hire substitutes, or they may have other distortion costs from such an arrangement. They might also have individual contracts with their workers obliging them to pay for wages above 6G during the maternity leave period, although this is not mandatory. Another source of indirect costs for the employers is if the workers are getting less productive from a period of absence due to maternity leave. The target of this paper is to explore whether such effects can be expected.

We will now move on to discuss the theoretical and empirical foundations for research on the theme of women, pregnancy, productivity and absenteeism to search for clues on how maternity leave might affect productivity.

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<sup>15</sup> It is estimated that real wages in Norway has increased on average by 1.9% every year since 1979 (Finansdepartementet, 2012a: 4.2).

## **3 Previous Findings on Maternity leave & Productivity**

Much of the focus of previous research relating to maternity leave has evolved around wages and employment, especially within economic research. Thus we are forced to consider many other potential sources to discuss the issue of maternity leave and productivity. We present several studies and discuss what predictions they make for productivity and maternity leave. One of the most relevant areas is the study on health consequences of childbirth, and how maternity leave might alleviate the potentially adverse health effects such an important occurrence has in a woman's life. We will first present these effects, which largely are considered to influence the productivity level of women, mainly through mental health, physical health, and the general vitality of women. We will later present the main economic studies on maternity leave and the labor market, which as previously mentioned focus mainly on wages, return rate, and employment. This serves the purpose of explaining how traditional free market economics makes predictions on how maternity leave affects the wages of women. Under some assumptions free market economics can say something about productivity as well. It is also interesting to say something about the employment of women as this can be an indication of how the women fare at work. If employment for instance is expected to drop after a period of maternity leave, it might indicate that women are no longer motivated or able to perform wage labor. We start of by discussing some relevant findings in the medical, psychological, and economics literature about the consequences of birth on a women's mental and physical health.

### **3.1 Health Consequences of Maternity Leave**

In a recent paper, Chatterji, Markowitz, & Brooks-Gunn (2011) finds that working while having 6 months old infants are positively linked to depressive symptoms and self-reported parental stress. Goetzel et.al. (2004) finds that depression has detrimental effects on productivity in the workplace. This suggests that maternity leave is necessary, not only for the health and well-being of the individuals, but also for how productive they will be at the workplace. It suggests that a period of maternity leave is essential for having a healthy worker returning after a childbirth which, implicitly, argues that productivity then will be higher than if the women did not have access to maternity leave.

### 3. Previous Findings on Maternity Leave & Productivity

Chatterji & Markowitz (2005) also found evidence that longer maternity leave periods are associated with a reduction in the frequency of depressive symptoms. They find evidence indicating that increasing maternity leave by one week is linked to a 6-7% decline in these symptoms. They use IV-estimation to control for endogeneity, because the choice to go back to work might very well be linked to depressive symptoms. They study a dataset from 1988, when the US was one of only two industrialized countries who did not have a national maternity leave policy. Hence the choice to take a period of leave was voluntary, and linked to other available policies (sick leave, temporary disability laws, etc.). This makes ideal conditions for studying the effects of maternity leave because it was not universal in the U.S. at that time.

In another study, McGovern et.al. (1997) explores how absence from work after a birth influence the postpartum health of employed women. They found that such absence from work, as well as many other factors such as hours of sleep per day, maternal illness, infant illness, social support (by spouses, friends and other family members), the level of difficulty in finding childcare, job satisfaction, and the level of physical exertion at the workplace influences mental health, vitality, and the level of limitations to role functions at the workplace and in everyday life. Limitations to role functions are directly relevant for how productive they are at work after childbirth. Role functions are measured as a scale of the combined effect of physical and emotional health problems, or fatigue, on an individual's daily activities (McGovern et.al., 1997: 510). For instance, more sleep (defined as hours of sleep per day) is significantly correlated with fewer limitations to role functions. Maternal illnesses are significantly correlated with more limitations to role functions. Infant illnesses are also significantly correlated with more limitations to role functions. Women who receive help with chores and childcare from their spouse, family, or others have fewer limitations to role functions. A higher job satisfaction and lower levels of physical exertions at work are also associated with fewer limitations on role functions.

All these problems are well known to families and mothers with infants. It shows that it is important that there is a network of support around the women, both for health reasons and for the women to be able to function properly at the workplace. Perhaps the most interesting finding is that McGovern et.al. (1997) found evidence of diminished levels of maternal well-being for employed women 7 months after the childbirth. For us this might indicate that the factors mentioned above influence productivity in a negative way for women upon return.

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Another interesting finding from McGovern et.al. (1997) is that they found a U-shaped effect from time off work. This means that initially less absence from work are associated with better health. But as time goes by, more absence from work is associated with worse health. This relationship reverses itself again at later stages of the postpartum indicating that as even more time goes by, more time off work is associated with better health. They propose that this relationship might be explained by unobserved levels of prenatal health. In other words, the ones who are very healthy before a childbirth are also the ones who need less time to recover and function at productive levels again after, while the less healthy needs more time to adjust. In Norway it is sometimes suggested that our women athletes are “better” when they return from childbirth. Instead of this being due to a motivating factor of becoming a mother, this might simply be explained by an endogenous health factor – these women are likely to be very healthy at the outset and needs less time adjusting to childbirth than the average woman.

In a recent study Herrmann & Rockoff (2012) finds evidence that health related absences for teachers’ causes a similar drop in student performance to other absences. Herrmann & Rockoff (2012) assumes that maternity leave is a consequence of adverse health reactions from giving birth, and includes this as one of their health related absences. Their main variable indicating productivity is students’ performance, and their goal is to compare maternity leave (among other health related absences) to other absences and see whether they are more detrimental to student performance due to preexisting health conditions. The assumption is that teachers with better health can be expected to be more productive at work, and exogenous absences such as funerals, weddings, and illness in the family, could be expected to have a less detrimental effect on productivity than absences due to health reasons. For us, their most important finding is that maternity leave, along with other absences, causes productivity to fall when measuring productivity in student performance (Hermann & Rockoff, 2012: 771). However, it is not very surprising that the absence of a teacher causes a drop in students’ performances since the measure of productivity is directly dependent on the period of absence. In our case, the measures of productivity are not dependent on the absence itself, but rather how the absence has influenced the workers ability to perform upon return. The results are therefore not directly comparable but the study gives us an indication that maternity leave can have similar negative effects on productivity as other absences. In addition it underlines the assumption that maternity leave causes detrimental health effects.



### 3. Previous Findings on Maternity Leave & Productivity

Another recent study (Carneiro et.al., 2011) gives us a view of how children are influenced by maternity leave policies. They show that the shift in maternity leave policies in 1977 led to an overall 2.7 percentage point decline in high school dropout rates and a 5% increase in wages for the children at age 30.<sup>16</sup> This clearly suggests that maternity leave is good for especially the children, and serves as another argument for the legitimization of the current scheme. Many other studies (Blau & Grossberg, 1992; Brooks-Gunn, Han, & Waldfogel, 2002; Waldfogel, Han, & Brooks-Gunn, 2002; Baum, 2003) have suggested that the cognitive development of children might suffer from maternal employment during the child's first years, and that this can lead to more behavioral problems.

#### **3.2 Labor Market Consequences: Can they Make Predictions about Productivity?**

We should also discuss some of the theoretical arguments that have been put forward on maternity leave and its labor market effects. We do this to search for possible clues on how productivity might be affected. Ruhm (1998), while following classical economic arguments, claims a voluntary maternity leave scheme based on private initiative might lead to adverse selection by women with a “high risk” of getting pregnant. He argues that they might self-select themselves to workplaces where these benefits are provided, and thereby giving rise to market failure (Ruhm, 1998: 288). However, as in our case maternity leave is provided by law for all employees, this argument is not directly relevant. Furthermore, it does not give any clue to whether productivity might rise or fall after a period of maternity leave. Ruhm also suggests a governmental initiative to compensate for this potential market failure (Ruhm, 1998: 289), much like the system we already have in Norway. His main suggestion from the article is that maternity benefits will either reduce both employment and wages, or simply just wages to compensate for the costs such a scheme will have on the companies.

This suggestion is not in large part affected by what Ruhm (1998) calls “dynamic effects”, such as depreciation of human capital (loss of productivity). Ruhm (1998) claims, from a theoretical perspective, that a loss of human capital would shift the demand curve for labor further to the left after implementing maternity leave if the employers build this in to their demand functions. This expected depreciation of human capital is also mentioned by Rønsen & Sundström (1996), which adds that the non-accumulation of experience due to a maternity leave should also lead to lower productivity and hence lower wages. Ruhm (1998), while

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<sup>16</sup> Review section 2.3 for a more elaborate discussion about the development of maternity leave in Norway.

### 3. Previous Findings on Maternity Leave & Productivity

analyzing this from a theoretical perspective with rational individuals, implicitly suggests that if there even are some productive gains, they are not important because the employers should in that case have built this into their demand function. Rønsen & Sundström (1996) and Lai & Masters (2005) also implies this in their respective articles – theoretically, if there is a shift in the demand curve due to maternity leave, then maternity leave is likely to have caused a depreciation of human capital. Hence we must note that while Ruhm (1998), Rønsen & Sundström (1996), and Lai & Masters (2005) are mainly focusing on wages and employment, they are expecting a depreciation of experience from maternity leave.

The Australian Productivity Commission suggests the opposite. They suggest that since maternity leave might increase the health and well-being of both mother and child, and also workplace morale (Australian Productivity Commission, 2009: Section 7.3), there might be some productivity gains for a company by allowing maternity leave.

This analysis serves the purpose of explaining the expected free market dynamics of maternity leave on wages and employment from a pure theoretical viewpoint. But we cannot say that labor market theory gives us any clear evidence on how maternity leave affects productivity. Their assumptions are based on rational individuals and decision making in the companies. To summarize, Ruhm (1998), Rønsen & Sundström (1996), and Lai & Masters (2005) expect wages to fall and if wages are a true reflection of marginal productivity, this should imply that productivity also falls.

### **3.3 Survey Results**

An interesting study conducted by Gueutal, Luciano, & Michaels (1995), and published by the Journal of Business and Psychology, tries to further explore how women actually fare at work during and after a pregnancy. Gueutal, Luciano, & Michaels (1995), while holding a predominantly psychological view, finds evidence that pregnant women receive better performance appraisal ratings during a pregnancy than before the actual pregnancy. They also find that pregnant women are rated better than the control group of non-pregnant women. They study an upstate New York bank, which resembles the company my dataset are collected from. The women in both cases have predominantly jobs which are not highly knowledge-intensive.<sup>17</sup> However, the authors are not certain that the improved ratings are because of higher performance by the pregnant employees or a more lenient view on their

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<sup>17</sup> Job tellers and customer services.

### 3. Previous Findings on Maternity Leave & Productivity

performance by their superiors (Gueutal, Luciano, & Michaels, 1995: 164-165). Perhaps even more interesting for us is it that the authors' finds that the after-birth levels on the performance ratings are higher than the before-birth levels. But this relationship is not statistically significant at the 10%-level (Gueutal, Luciano & Michaels, 1995: 163).<sup>18</sup> These results might, if the performance ratings are actually reflecting true performance, indicate that productivity might be higher after than before a pregnancy. The authors suggest that there is potentially a "pregnancy effect" which translates into a more lenient view from their superiors, and that the slightly higher performance rating in the period after the pregnancy might be a spill-over effect from this (Gueutal, Luciano, & Michaels 1995: 164). The problem with this study is hence that we might see some bias in the results because of secondhand reporting by the women's superiors.

Halpert et.al. (1993) reports the opposite, namely that pregnant employees receive significantly lower performance ratings during pregnancies than at other points in time of their work-lives. They found, by asking participants to observe videos of women working during and after pregnancies, that participants gave lower performance ratings to women during their pregnancies than after. However, this does not give any indication whether the employees were more productive after than before their pregnancy.

Brown et.al. (2002) explores the relationship of pregnancy status to job satisfaction. Their findings indicate that the job satisfaction of the individuals in their sample was significantly greater before their pregnancies than either during or after. They also find that job satisfaction was significantly and positively correlated with organizational maternity leave policies. In addition they found that while 80% of their participant indicated that their career goals had not changed after they became mothers, 70% reported that their ability to do their jobs did not change. This difference is low, but it is interesting to see that while many of the women had not changed their motivation, a slightly larger percentage indicated that their ability to do their work good had changed. However, this study had many weaknesses. For one thing their data was retrospective; participants were asked to answer on a basis of having a child in the last 5 year and responding to whether they felt satisfied with work before, during, and after the pregnancy. This may, as the authors themselves suggest, be subject to cognitive distortions. In addition their sampling was not random, nor representative of all types of jobs held by pregnant women. They also had a very low sample size ( $N = 43$ ). In conclusion, the study

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<sup>18</sup>  $p=0,130$

### 3. Previous Findings on Maternity Leave & Productivity

has limited implications due to its significant weaknesses. Nevertheless it serves as an indication that if job satisfaction declines during and after a pregnancy, we might also expect productivity to be declining.

#### **3.4 Can the Return Rate Make Predictions About Productivity?**

Waldfogel et.al. (1999) argues that maternity leave increases the likelihood that a woman returns to her former workplace after a birth, compared to those who do not receive similar coverage. The hypothesis that women are more likely to return to the workplace after a maternity leave is also supported by findings from Norway and Sweden (Rønsen & Sundström, 1996). Stanfors (2003) adds to this research proposing that women with higher education have a higher propensity to return to the workplace. She also adds religious affiliation to the equation, proposing that religious women might have a lower propensity to return to the workplace.

There seems to be an agreement in the literature that, all else equal, maternity leave will increase the likelihood of returning to their former workplace. This suggests that the health benefits from being able to have a period of maternity leave might help these women to return. However, it gives few direct clues on how they actually perform upon return.

#### **3.5 Can Wages Make Predictions About Productivity?**

Some evidence (Waldfogel, 1997; 1998; Joshi et.al. 1999) shows that there have been positive wage effects of returning to the same employer in Britain and the U.S. Isolated this could support a claim that the women become more productive when returning, especially if we see wage as a reflection of marginal productivity. This could for instance be explained by increased wage ambitions because of the increased burden of providing for a family.

On the other hand Waldfogel et.al. (1999) also suggests that “*If maternity leave policies allow women to take more time away from work, then they might result in lower pay for the women involved due to the loss in work experience,...*” (Waldfogel et.al., 1999: 531). This is a suggestion drawn from the implication that time off work leads to lower productivity (through a drop in human capital) which in turn leads to lower wages. Traditional economic theory seems to not have been too preoccupied by productivity changes of maternity leave, perhaps because traditional economic theory suggests that reduced experience, the riskiness of hiring young women, and distortion costs for companies, will reduce wages. This is in many

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situations seen as a reflection of the workers' productivity, or more specifically their marginal productivity (see f.ex Rønsen & Sundström, 1996; Ruhm, 1998; Lai & Masters, 2005). It is therefore implicitly assumed that productivity will fall after having been away at maternity leave, and hence it has not been an interesting subject to research. Another explanation is that it is difficult finding good measures of productivity. Our study is therefore in a special position, because it has access to direct measures of productivity (sales, frequency of picked up telephones, value of sales) and direct measures of input (minutes logged in to the sale system).

Lai & Masters (2005) also finds evidence that in Taiwan the wages of young women are lower in the sectors covered by maternity leave legislation compared to men and older women. But this does not necessarily imply that such workers are less productive than others. Again, it can also be explained by companies setting their wages lower to compensate for the costs the companies will have in finding a replacement, training that person, and enduring the inevitable period of low productivity while the replacement are learning the job.

Zhang et.al (2013) finds some evidence that a high degree of absenteeism results in lower productivity and wage. The authors also find evidence that reduced wage due to absenteeism underrepresents the reduced productivity for workers in teams (Zhang et.al., 2013: 30). Essentially this means that when workers are paid on their team performance, wages cannot be expected to represent marginal productivity. Zhang et.al. (2013) uses the example of when a surgeon is absent. If the surgeon is essential to the surgery the team of nurses and other medical employees might be restrained from doing their job, hence the productivity loss is not only the surgeons' wage alone but the value of the output of the entire team. The employees in our study works in teams, thus we might expect that for us wage is not a good measure of marginal productivity. Another importance of their findings is that wages underrepresents productivity in general; this indicates that wages may suffer from a downward bias in measuring marginal productivity.

In a recent study, Cools & Strøm (2011) finds that women with higher income reduce their work-hours relatively less after birth. They also find that the importance of wage changes after childbirth. Women have more positive own-wage elasticities and more negative cross-wage elasticities relative to their husband. This essentially means that wage becomes increasingly important when deciding between work and staying at home after having a child.

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The fall in cross-wage elasticity means that after having children, family members substitute working hours between each other more than before to financially adapt to this new situation. We may thus expect different productivity reactions depending on the wage level and ambition of the women after maternity leave. Women in the higher income group might be expected to work more in order to not depreciate their human capital, and thus remain at a high wage level, while the opposite can occur with women earning less.

Markussen (2012) presents evidence suggesting that in Norway, a 1 percentage point increase in a worker's sick leave causes earnings to drop by 1,2% two years later. He also finds evidence that around half of the reduction in earnings can be explained by a reduction of around 0.5 percentage points in the probability of being employed. Hence Markussen (2012) finds evidence that the effects from a sick leave on employment can only partially explain the reductions in earnings. The rest, he suggests, is explained by employers taking into account the inherent productivity of the worker and setting their wages based on this (Markussen, 2012: 1288). By using the leniency of primary care physicians as an instrument for sick leave he uses a dataset of approximately 3.94 million employees and convincingly estimates the causal effect of sick leave on pay. He works under the assumption that due to individual wage bargaining at the workplace, the sick leave either depreciates the individuals' human capital leading them to be less productive, or signals a less productive imagine to the employers causing them to reduce wages. If in fact the wages are, at least over time, a reflection of the worker's inherent productivity one might suspect that since sick leave reduces pay (and thus productivity) perhaps maternity leave will do the same. But it is worth pointing out that Markussen (2012) finds a less clear reduction in wages for women. He suspects that this might be because women are perceived to have a more legitimate claim to sick leave due to reasons of family and health (see also Inchino & Moretti, 2009).

In some cases one might expect that the need for better financial coverage when having to care for a child might induce parents to work harder and be more productive. If we are assuming that wages are reflecting the marginal productivity of the employee then we might see some of the evidences presented here as an indication against the validity of this argument.

A last argument worth pointing out is that many workers face a certain quota or defined goals of achievement at work. If a woman has young children she might be inclined to perform

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more efficiently at work in order to fill this quota because she must be more efficient in allocating time between the various tasks and roles she is assumed to fill. However, we find no support for this argument in the literature, although the argument might be well founded.

#### **3.6 The “Double Burden” Hypothesis**

Some authors have claimed that today when women are becoming increasingly likely to take part in the workforce after a birth compared to the past, they are also more likely to take on a “double burden” meaning that they still have the main responsibilities at home (see for instance Hochschild, 1997 or Rieck & Telle, 2012). Such a “double burden” could be suspected to influence the productivity of women at work as well as at home. Working two jobs, one as a homemaker and the other as a career woman, clearly has some obvious difficulties and can potentially have negative effects on the productivity while at work.

Rieck & Telle (2012), using data on all Norwegian women giving birth from 1995-2008, finds that women’s sick leave increases after the birth, but when controlling for selection issues this increase dissolves itself. Hence they conclude that there is no evidence of any impact of such a “double burden” on the sick leave of Norwegian women. But this is not a rejection of the effect of such a potential “double burden” on productivity *while at work*. Such an effect might still be there even though the women cannot be proven to be more often sick. The natural consequence from such a “double burden” would be reduced productivity, the women becomes overloaded with work on two fronts and/or stressed, which would render them potentially less productive. However, as the existence of such a “double burden” is contested (Craig 2007: 150), we shall not further investigate whether this effect is true or not. Rather we can pinpoint its relevance and potential predictions about productivity. If indeed women are suffering under such a double burden we might expect it to influence their performance at work.

#### **3.7 Conclusion: What Predictions Can We Make For Productivity?**

From the discussion above it seems likely that while perhaps not maternity leave *in itself* is having a detrimental effect on productivity, giving birth might. It seems well documented that giving birth can lead to adverse effects on a woman’s physical and psychological well-being as well as performance at work. There is some evidence that maternity leave is ameliorating these effects (Chatterji & Markowitz, 2005). But overall there is a consensus that due to the effects from such a life changing event, and the potential health problems caused by this, a

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woman's productivity might be affected in a detrimental way (McGovern et.al., 1997; Chatterji, Markowitz, & Brooks-Gunn, 2011; Hermann & Rockoff, 2012).

There is some evidence suggesting a positive effect from maternity leave (Gueutal, Luciano & Michaels, 1995) but most other studies either implies that maternity leave will lead to a depreciation of human capital (Rønsen & Sundström, 1996; Ruhm, 1998), or find suggestive evidence for this (Halpert et.al., 1993; McGovern et.al., 1997). The most interesting debate essentially revolves around whether maternity leave is similar to other kind of leaves, such as sickness leave, which have been shown to have a detrimental effect on wages and marginal productivity (Markussen, 2012; Zhang et.al., 2013). Hermann & Rockoff (2012) finds some evidence that maternity leave has a similar effect as other absences on productivity.

While maternity leave might plausibly be argued to have the potential of increasing the return rate to work and ameliorating negative health effects, it is harder to argue that it will *increase* productivity compared to before birth. Although one might expect it to slow down the process of decaying productivity. Considering the many obligations women face today, such as expectations of being a productive and ambitious worker while at the same time being culturally exposed to take the weight of tasks at home, expecting a period of increased productivity after a maternity leave might be misguided. An interesting subject to research would be to compare the women that did not have any maternity leave with the ones who had and see how their productivity was affected comparatively. This could give indications to how the effect of maternity leave truly is. However, this is difficult since in most cases maternity leave is provided by law and a division into one treatment group that receives maternity leave and another that does not is not feasible.

The predictions of former literature for maternity leave and its effect on productivity are thus rather gloomy. Our study is in a good position to test such predictions, but we face certain problems. One of them is that Norway is not very generalizable to the rest of the world when it comes to maternity leave. Another problem is that we are not studying a whole host of companies but a single one with its particular characteristics. However, this study might give an indication to what many other researchers have resorted to simply assume in the past, namely how productivity is affected from maternity leave.



## 4 Data

Our dataset contains observations from the Norwegian branch of an international insurance company. The observations are taken from the sales and customer service department. The employee's tasks are to help existing customers regarding their existing insurance policies and also to propose new insurance products for the customers calling the company. Customers' requests are handled by telephone, no calls are supposed to originate from the call center if not due to gathering of information in order to help the customers. This means that when the employees are acting as sellers they are not actively seeking customers but are left to sell to the customers calling them. The sellers are also evaluated on the value of their sales. No further information about the company will be presented due to issues of anonymity.

### 4.1 Unit of Observation and the Organization of Data

The observations are from the time period of 2003-2009 and contain a total of 332 weeks.<sup>19</sup> The time variable in our case is weeks. The dataset is a panel data where we follow the same individuals over time. The data is unbalanced, which means that the individuals worked in the company at different time periods and for different amounts of time ranging from 2 to 323 weeks. The average number of weeks we have observations from is 104.3, or around 2 years. This only included the weeks where the employees logged on to the internal telephone system – we have therefore excluded weeks where the workers were absent the entire week. Due to the fact that we want to study maternity leave we have excluded men. The percentage of men in society who are absent for parental leave are in our opinion still too small to be studied efficiently. However, this might be an interesting field for further research. The number of women who have registered observations in the observation period is 256.

The job is to some degree mechanical, which means that the tasks are not highly knowledge intensive. This might also explain the somewhat low degree of continuity in this specific branch of the company.<sup>20</sup> Many employees could be expected to use this job as a stepping stone towards other, and perhaps more attractive jobs, within the company or move on to other similar companies as well as changing jobs. However, it is worth pointing out that

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<sup>19</sup> The first week of January 2003 is coded as week 1, while week 332 then becomes week 20 of 2009, the third week of May 2009.

<sup>20</sup> 2 years excluding both holidays and weeks when the employees were absent the entire week. However, the degree of continuity might not be as low as first mentioned when looking at this specific sector, in fact opinions expressed in the media has specifically said that employees in this company is rather loyal. Sources will not be disclosed due to issues of anonymity.

Aarbu & Torsvik (2007), while studying the same company, argues that the tasks the employees perform are rather difficult in some circumstances because of the nature of the products they are selling. They are not supposed to sell as much as they possibly can, but efficiently “screen” potential customers into the right kind of insurance packages. This is in line with traditional theories about the adverse selection and moral hazard problems facing companies, and especially insurance companies.<sup>21</sup> The consequences this has for our analysis are that number of sales alone is not necessarily the best measurement for productivity. We need to consider that the workers are not supposed to sell as much as possible, but also to the right customers.

## 4.2 The Dependent Variables

Our dependent variables, and thus measures of productivity, in this study are the sales made, the value of the sales (*Premiums*), and telephones answered. Below we have made some adaptations to how we structure these variables. It is not only the goal for this company to sell the most products, but also to help the customers. It therefore does not make sense to simply look at the number of sales as a measurement of productivity. In that same respect, it does not make sense to look only at the number of telephones answered or the value of sales. We have to bear in mind that we also have the problem of adverse selection in the insurance industry. Below we further discuss how we can try to measure productivity in this complex environment where not only sales, but also the value of sales and the importance of simply answering customers’ requests, are modeled.

Our main specification will be to create 3 new variables. These variables are “*Telephones per hour*”, “*Sales per hour*” and “*Premiums per hour*”. Creating these variables follows the traditional way of measuring productivity by linking input to output (Mark, 1982). Measuring especially output has caused serious measurement difficulties in earlier studies (Mark, 1982), but we are in a position where we have quantitative data on both input and output, making it possible for us to measure productivity more accurately.<sup>22</sup> However, we must also be aware that when selling products the employees are faced with paperwork and other “follow up” tasks which renders them unable to log on to their system. This would in our case lead to an upward bias in analyzing the “per hour” variables due to the possibility that the denominator falls when sales are high, creating a possibility that we are overvaluing the productivity of the

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<sup>21</sup> See for example Hindriks & Miles (2006) for a more elaborate discussion on this subject.

<sup>22</sup> Input is hours worked.

relevant employee. We can thus establish that there are weaknesses with these “per hour” variables also; they are not perfect even though they might be more reasonable than just presenting the quantitative values of sales, value of sales, and telephones answered.

We cannot either entirely circumvent the problem that within the company productivity is not entirely defined by having the highest sales rate. We have to carry these two main problems with us. The employees’ need to “screen” potential buyers, and the need to also perform simple customer services as well as sell products.

Below we present the dependent variables and an explanation of them.

**Table 1: The Dependent Variables**

<b>Dependent Variables</b>	<b>Explanation</b>
<i>Sales</i>	<i>Sales per week (Integer)</i>
<i>Telephones</i>	<i>Telephones answered per week (Integer)</i>
<i>Premiums</i>	<i>Sales in NOK per week (in hundreds)</i>
<i>Telephones per hour</i>	<i>Telephones answered per hour</i>
<i>Sales per hour</i>	<i>Sales made per hour</i>
<i>Premiums per hour</i>	<i>Sales in NOK per hour</i>

To summarize, we have decided to use the direct effects from maternity leave when observing the quantitative levels of our productivity variables, but we will also check the perhaps more valid indicators of productivity; namely how these variables interact between input and output. Another reason for this linking of input to output is that sick leave might increase after maternity leave rendering the individuals not present for a full week after the period. We will discuss the validity of our dependent variables and compare them more below in section 6.7.

### 4.3 Descriptive Statistics

In the sample we have a total of 58 women who gave birth once or more during the observation period, while 198 did not. We do not have information prior to 2003 which means some of the women might have had children previously, but this is not accounted for here. We have data on the first, second, and third birth if the women were still employed in the company when giving birth.

**Table 2: The Birth Rate in the Observation Period**

	Women (N)	Percentage (N)	$N * T$	Percentage ( $N * T$ )
<b>Gave birth</b>	58	22.66%	7478	28.01%
<b>Did not give birth</b>	198	77.34%	19219	71.99%
<b>SUM</b>	<b>256</b>	<b>100.00%</b>	<b>26697</b>	<b>100.00%</b>

*Note: N refers to the individuals while T refers to weekly observations. Hence we see that even though the amount of women giving birth were only 22.66% of the total amount of women in the sample, the total amount of observations we have from this group is 28.01%.*

We observe that approximately 23% of the women gave birth once or more during the employment period. In total, approximately 28% of the observations are from this same group. This percentage is relatively high so we can conclude that this number will be sufficient to get a representative view of productivity before and after a period of maternity leave. If there is a connection between maternity leave and productivity, this study might give an indication to the direction of this and if this connection is significant.

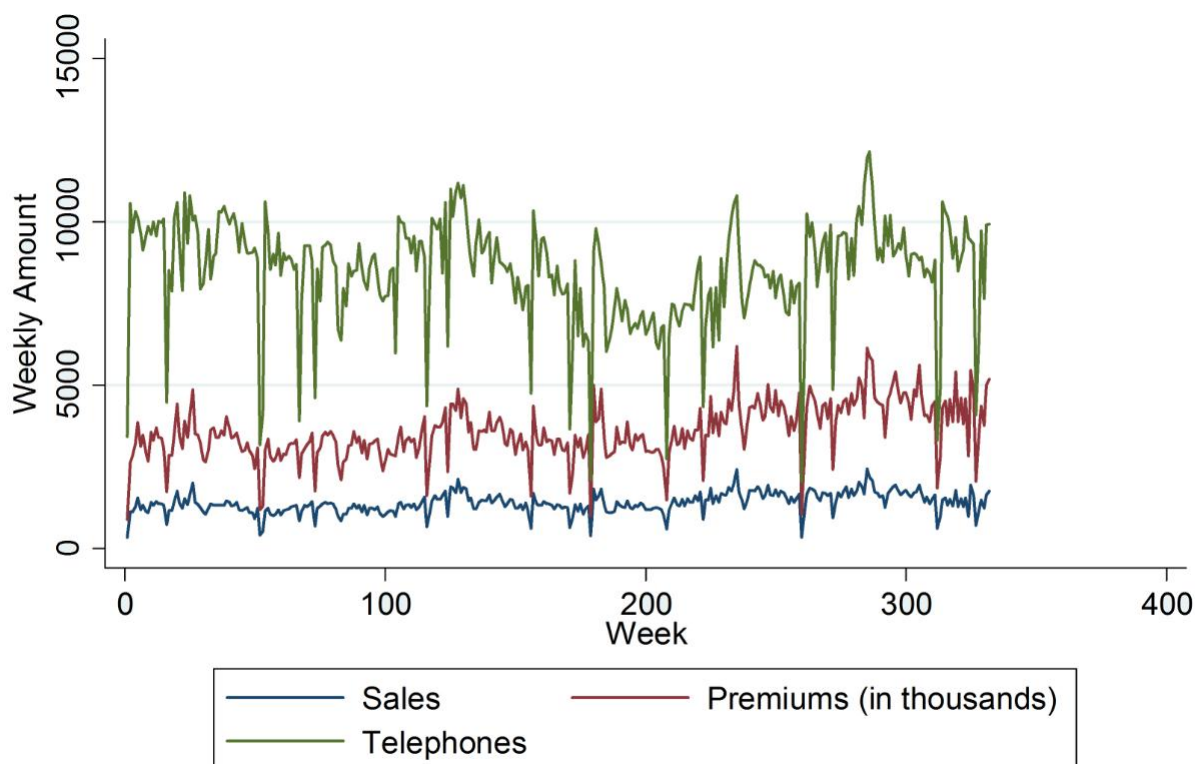
We will now continue exploring the body of the data before we can analyze its function with econometric methods. We see under, in *Table 3*, the average sales, the average value of sales, and the average telephones answered for the employees during the employment period. We also observe the minimum and maximum observations for each variable.

**Table 3: Average Sales, Premiums and Telephones Answered in the Observation Period**

	Observations ( $N * T$ )	Mean	Standard deviation	Min	Max
<b>Sales</b>	26697	17.22	14.2	1	110
<b>Premiums</b>	26697	443.92	384.11	1	4000
<b>Telephones</b>	26697	105.62	79.2	0	564

*Note: Premiums are reported in hundreds in Table 3.*

During the observation period the average weekly sales were approximately 17, the average weekly value of sales were 44 392 NOK, and the average weekly answered telephones were 106. There is a great discrepancy between the lowest and the highest number of sales, telephones answered, and value of sales. This gives us an indication that the variables *Sales*, *Premiums* and *Telephones* differ a lot between the individuals. We also know that from some of the weeks we have 0 reported answered telephones. The standard deviation indicates that there is great deviation from the average, and that all our productivity variables vary a lot from week to week. Below we see the development of *Sales*, *Premiums* and *Telephones* during the observation period.

**Figure 4: Weekly Development of Dependent Variables in the Company**

Note: The difference is reported in weeks and is only for the women in the company, not the men, so company averages would be different.

The weekly data reflect that the average sales, value of sales and telephones answered by women in this particular company were fairly constant over the weeks.<sup>23</sup> In *Figure 4* we have not controlled for seasonal trends. When performing the analyses below we have controlled for time-specific effects which will reduce the effect from seasonal variations. The company will naturally have much lower values for *Sales*, *Telephones* and *Premiums* during holidays, so this can explain much of the variation we see above, although the general trends seem to be rather flat over the entire period in question. The most important thing to observe from this figure is that there are no observable general negative or positive trends over the observation period, although we see a slight increase in the value of sales.

To further distinguish the relevant groups from each other, we will now present the average sales, telephones answered, and value of sales for the women who gave birth during the sample period and the women who did not.

<sup>23</sup> The regular drops in the data causing volatility are suspected to be due to seasonal variations.

**Table 4: Averages in Dependent Variables Between Those Giving Birth and Those Not**  
**Women Who Gave Birth vs. Women Who Did Not**

N*T=7478, N=58	<i>All women who gave birth</i>				
	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	16.31	14.74	1	110
	Telephones	101.96	87.61	0	461
	Premiums	421.68	409.65	1	4000
N*T=19219, N=195	<i>All women who did not give birth</i>				
	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	17.56	13.98	1	110
	Telephones	107.05	75.63	0	564
	Premiums	452.58	373.36	1	4000

*Note: This table depicts the averages for women who gave birth once or more during the observation period and for the women who did not. Note that this is not our comparison and treatment group because the observations before birth will also be part of the comparison group when analyzing.*

We can deduce from *Table 4* that on average the women who gave birth were slightly less productive than the ones who did not. We see that the average sales were slightly more than 1 sale lower for the women who gave birth than in the other group, they answered approximately 5 fewer telephones weekly, and sold on average products worth 3090 NOK less than the other group on a weekly basis. But we must bear in mind that we have not controlled for trends, so we should be careful to put any significant weight on these numbers. In addition, this is not in fact our control and treatment group as we shall see below. However, it does give us an indication on how productive these two groups are. The standard deviation again indicates great variations from the average. The standard deviations are slightly higher for the women who gave birth which indicate that there are high variations from the average here.

Below we show a within-groups table portraying the average sales, average value of sales and average telephones answered before and after the *first* child for the women in the data who gave birth:

**Table 5: Averages in Dependent Variables Before and After Birth**

		<b>Women Who Gave Birth</b>			
		<i>Before first child</i>			
N*T=4507, N=58	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	18.68	13.84	1	108
	Telephones	123.07	84.86	0	461
	Premiums	473.71	375.55	1	2935
		<i>After first child</i>			
N*T=2971, N=55	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	12.72	15.32	1	110
	Telephones	69.94	81.83	0	446
	Premiums	342.75	445.15	1	4000

*Note:* We see that 3 individuals do not return after their first child.

First off all, we observe that some of the women who became mothers during their employment at this company did not return, and that the number of weeks worked after a period of maternity leave was lower than before.<sup>24</sup> This might reflect that many of the employees are young and perhaps using this specific workplace as a stepping stone towards other more attractive jobs. In addition, some women moved on to other positions within the company in other departments. After the pregnancy it might also be likely that some of them started a life as a homemaker.<sup>25</sup> In our case this is not necessarily a problem, in fact it seems like since there is a considerable amount of women returning it leaves some circumstantial evidence for hypothesizes about high retention rates in cases where maternity leave is provided.

The data seems to be telling us that the women returning from maternity leave answer less telephones, they seem to sell fewer products, and they are selling less valuable products than earlier. There is especially a great discrepancy in telephones answered before and after maternity leave. But these data do not show us the development in our dependent variables over time, they simply shows us an average over the time periods. It is therefore not giving us

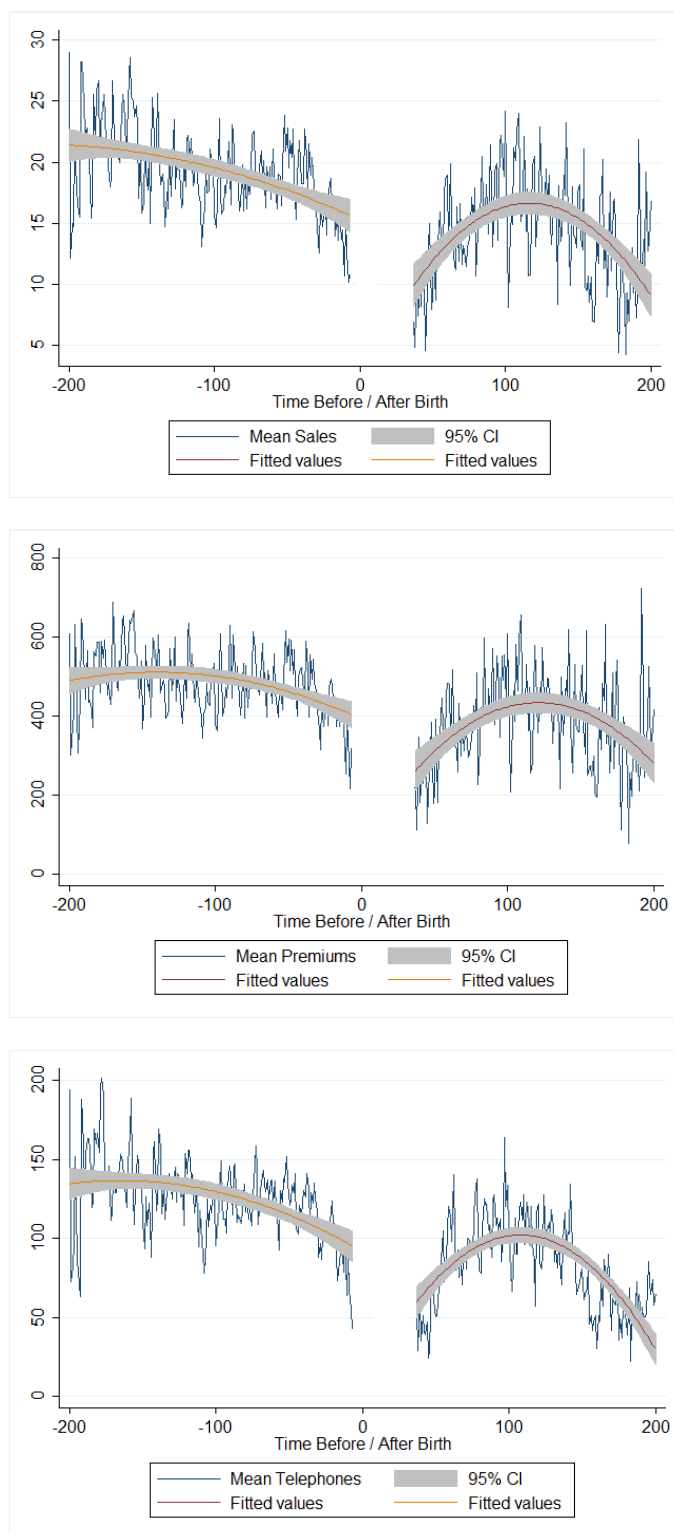
<sup>24</sup> On average, women worked for 77.7 weeks before having their first child. The individuals that returned worked on average for 54 weeks after returning from their first maternity leave.

<sup>25</sup> The tradition of being a housewife in Norway is not very indebted in Norwegian society. Full childcare coverage provided by the government, and the cultural norm that women are supposed to contribute equally in Norwegian work life, are likely causing many of these women to either return or search for other jobs after a birth.

any definite answers to our final question whether women become more or less productive after a maternity leave. However, the data are an indication that these women might become less productive after the absence. The standard deviation again shows great variation around the average.

Below we show how the sales, telephones answered, and value of sales developed over time for the women that had children before and after the first child.



**Figure 5: The Before/After Premiums, Sales & Telephones**

*Note: The interval is discontinuous because the values between the 7<sup>th</sup> week before birth and the 37<sup>th</sup> week after birth are dropped. More about this is section 4.3.1. The trend is also limited to between the 200<sup>th</sup> week before birth and the 7<sup>th</sup> week before birth, and the 37<sup>th</sup> week after birth and the 200<sup>th</sup> week after birth, due to few observations before and after these points. The time variable is not the same as in Figure 4 above, but a constructed time measurement (in weeks) for illustration of the weeks spent at work before and after a birth and subsequently a period of maternity leave. The equivalent of Figure 5 for Sales per hour, Telephones per hour and Premiums per hour (Figure 23) can be found in the appendix B1.*

*Figure 5* shows a slightly decreasing trend in all our main productivity variables. We have added a quadratic trend line to the figure and indeed this seems to fit the values quite well. Observing the figure, we see that the mean values are very volatile above the 200<sup>th</sup> week after a birth as well as before the 200<sup>th</sup> week before birth; hence these observations are not included when including a trend. This figure shows that it seems likely that after a birth, and consequently a period of maternity leave, the productivity is initially low before it increases and subsequently decreases again. The reason for this can for example be that the women returning needs a period of adjusting before they can reach the pre-birth levels of productivity. After a period of adjusting and a return to higher levels of productivity, the productivity again decreases. Why this happens is puzzling but it might be, as proposed by Rønsen & Sundtröm (1996) that the depreciation of human capital during the absence might not be fully compensated for upon a return. For example the women might be too preoccupied with their duties at home so the focus on performing well is not like it used to be. Another explanation is that perhaps the ambition level has dropped. We will discuss these issues more when performing the analysis below, but again this is not in fact our comparison and treatment groups as we shall see. When controlling for time at work and performing the same analysis on *Telephones per hour*, *Sales per hour* and *Premiums per hour* the trends are not deviating from *Figure 5* above. Hence this result seems to be valid also when controlling for actual time at work. *Figure 23* is reported in Appendix B1.

Below we show the development in productivity over the weeks for the comparison and treatment group we use in our sample. Our comparison group is all the women in the sample that had not yet given birth, and perhaps never will, while our treatment group is the group that has returned from a period of maternity leave. Hence all the observations from individuals which are taken at a point in time when this particular individual has not had a maternity leave, regardless of whether she will or not, is the comparison group in our sample. The treatment group is all the observations from an individual who has returned from a period of maternity leave.

**Table 6: Averages in Dependent Variables for Comparison & Treatment Group**

<b>Between Groups</b>					
N*T=23726, N=251	<b><i>Comparison Group (all observations from women who not yet/never had maternity leave)</i></b>				
	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	17.78	13.95	1	110
	Telephones	110.09	77.72	0	564
	Premiums	456.59	373.86	1	4000
N*T=2971, N=55	<b><i>Treatment Group (all observations from women who had a minimum of 1 maternity leave)</i></b>				
	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	12.72	15.32	1	110
	Telephones	69.94	81.83	0	446
	Premiums	342.75	445.15	1	4000

*Note: 251 individuals started off in a period before maternity leave, while 5 individuals started off just returning from a period of maternity leave. 55 individuals gave birth either right before the sample, or in the sample, rendering them the treatment group. We thus have 50 individuals which had observations both before and after a period of maternity leave.*

We clearly observe that our treatment group on average seems much less productive than our comparison group. All the values of our main dependent variables are lower for this group. This gives an indication to what we shall see when we perform the regression analyses below. The standard deviations are still indicating a large variance from the mean.

Before we look at the independent variables and start our analysis we will take a look at the density of our dependent variables. We do this just as much as a control of the reporting done by the company, as for observing them.

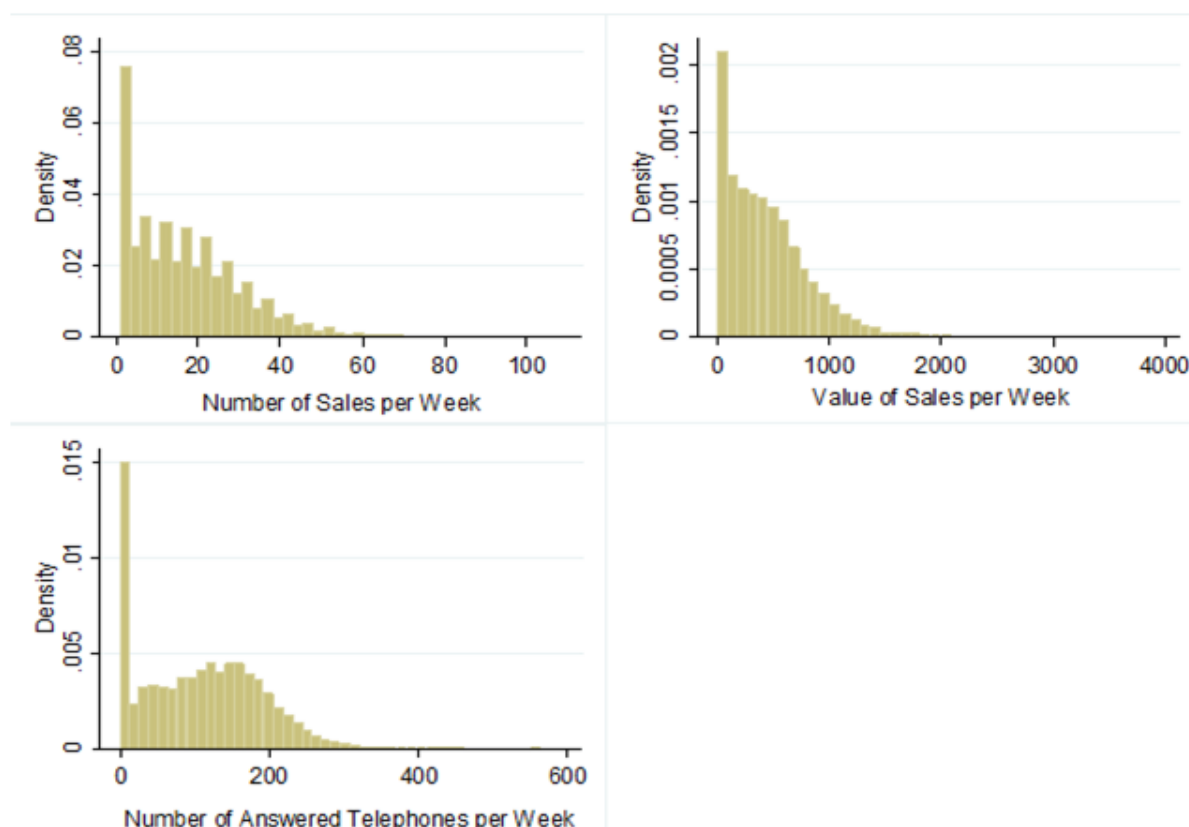
**Figure 6: Histogram of the Density of the Dependent Variables**

Figure 6 shows us a quite similar development between *Sales* and *Premiums* while a somewhat strange development in *Telephones* answered per week. We observe a very large density around few telephones answered per week which seems quite strange when considering that this is how they sell their products. In fact when tabulating *Telephones* we observe that 4383 weeks are reporting 0 answered telephones. Hence it might appear that *Telephones* is a variable which is behaving somewhat strange and are thus perhaps not a good measure of productivity. We suspect that this is due to some reporting errors in the company, but it is not important for our other two variables: *Sales* and *Premiums*. They seem to behave as expected. As suspected the histogram plot shows that most observation is located to the left in the diagram. The lowest values are most common, while some weeks have observations at the far right hand of the scale, where high sales or high values of the sales are registered. Below we show the difference in the dependent variables from the comparison group and treatment group:

**Table 7: A Summary of the Difference Between Comparison & Treatment Group**

<i>Variables</i>	<i>Mleave = 0</i>	<i>Mleave = 1</i>	<i>Diff</i>
Sales	17.78	12.72	-5.06
Telephones	110.09	69.94	-40.15
Premiums	456.59	342.75	-113.84
Sales per hour	0.660	0.464	-0.196
Telephones per hour	3.869	2.509	-1.36
Premiums per hour	17.214	12.587	-4.627

*Note: The control group is all the individuals which did not yet give birth or never did during the sample; the treatment group is the individuals that gave birth once or more during the sample and returned from a period of maternity leave. The numbers are hence the same as in Table 6 above with the addition of values for Sales, Premiums and Telephones per hour.*

Table 7 seems to suggest that the individuals who are back from a period of maternity leave are less productive than our comparison group. But we cannot yet say if this difference is significant, this is what we will estimate below. We also need to observe the differences over time within the groups to estimate the difference-in-difference estimator.

#### 4.3.1 Adjustments to the Data

One area of concern is that some of the observations are from the weeks just after a birth or just before. Hence, we have some observations at certain times from women that gave birth before they should have returned from their normal maternity leave period. We suspect that some of these observations are from women just checking up on work they left behind before they had their child. Hence, below in the analysis we need to make more adjustments to our explanatory variable and in fact, as we shall see, we end up removing some observations that are gathered within the normal period of maternity leave. We follow the same logic as with Figure 5 above, and remove the observations gathered from the weeks after the 7<sup>th</sup> week before birth and before the 37<sup>th</sup> week after birth when performing the analysis.<sup>26</sup>

<sup>26</sup> The reason we are dropping observations between and including the 6<sup>th</sup> week before and the 36<sup>th</sup> week after is connected to the maternity leave laws of Norway at this period of time, see section 2.3. Women must use 3 weeks before birth and 6 weeks after birth. The reason we have dropped 6 weeks before birth is that many women are allowed to use more time pre-birth than 3 weeks, and due to the amount of choice in the system we must therefore make a distinction between certain weeks that we consider potentially too volatile and not representative of productivity. We have to be open in our conclusions that especially our changing effects analyses below are very sensitive to how many weeks we chose to drop. The 36<sup>th</sup> week after is chosen because this gives a normal period of 42 weeks but bear in mind that some weeks are reserved for the father as well. Thus, we might have kept more weeks but a distinction is set here.

Another issue of concern is that some of the individuals we observe do not return from the maternity leave.<sup>27</sup> We also have some individuals who gave birth in week 1. This subsequently places them in the treatment group, yet we do not have any values from these individuals from before the treatment.<sup>28</sup> In addition, we also have some individuals who gave birth in the last week of the observation period.<sup>29</sup> In total there are 13 individuals who have few or no observations after the maternity leave, only have observations after the maternity leave, or gave birth at the last week of the sample period. One problem with the individuals who have few observations from after the maternity leave period is that these individuals might be at work for other purposes than selling or picking up telephones. They might for instance be brought in to advice or train new workers, or they might simply be “clocking in” to take care of administrative work or follow up previous sales. Hence, we must be open to certain errors here. We do not drop these individuals but we have to be aware that we have some individuals in the sample that never returned from maternity leave and hence had no observations after such a time. We also have to take into account that some individuals never had any observations from before maternity leave. We solve this by placing the individuals who gave birth before the sample period started in the treatment group for the entire period, while the individuals who gave birth at the end of the sample are coded as never leaving the comparison group. The individuals who never returned are coded as being in the comparison group, simply because we do not have observations from after their maternity leave period.

We present some descriptive statistics from the treatment group and the comparison group after we have done these adjustments to the data. By dropping all observations within the timeframe of -6 to 36 weeks after the individuals gave birth we are dropping 559 observations from our data which are deemed not relevant and not representative of the individual’s level of productivity. In total we thus have 26 138 observations. Below in chapter 6 we will discuss further about the consequences for especially our analysis on changing effects from maternity leave of dropping these individuals. Below we show the averages in the dependent variables when we have removed these 559 observations from our sample.

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<sup>27</sup> These are the individuals coded: 32, 379, 464, 491, 523 & 569. These individuals have 5 or fewer weeks of observations after the maternity leave.

<sup>28</sup> These are the individuals coded: 37, 111, 290, 322 & 476.

<sup>29</sup> Namely the individuals coded 191 & 219.

**Table 8: Averages in Dependent Variables after Adjustments for Comparison & Treatment Group**

<b>Between Groups (after adjustments)</b>					
N*T=23619, N=250	<i>Comparison Group (all observations from women who did not yet/never took maternity leave)</i>				
	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	17.81	13.97	1	110
	Telephones	110.33	77.72	0	564
	Premiums	457.38	374.03	1	4000
N*T=2519, N=44	<i>Treatment Group (all observations from women who had a minimum of 1 maternity leave)</i>				
	<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>
	Sales	14.44	15.66	1	110
	Telephones	81.32	82.22	0	446
	Premiums	390.35	459.34	1	4000

*Note: In total we still have 256 women in our dataset, 6 of these women had the value 1 for maternity leave at all their observations and are thus only part of the treatment group. 250 had observations either before their maternity leave period or never gave birth. In total 44 women had observations after the 36<sup>th</sup> week from their birth (hence compared to Table 6 above, 6 of the individuals did not have sufficient observations after the 36<sup>th</sup> week of maternity leave, and thus 6 of the individuals falls out from our treatment group but not the comparison group). In total 38 individuals had observations both before and after a period of maternity leave.*

We can see from Table 8 that there are large differences in averages also when dropping the problematic observations gathered within the normal period of maternity leave. We have summarized these differences between our treatment group and comparison group after the adjustments to our variables below.

**Table 9: A Summary of the Difference after Adjustments between Comparison & Treatment Group**

<i>Variables</i>	<i>Mleave = 0</i>	<i>Mleave = 1</i>	<i>Diff</i>
Sales	17.81	14.44	-3.37
Telephones	110.33	81.32	-29.01
Premiums	457.38	390.35	-67.03
Sales per hour	0.66	0.53	-0.13
Telephones per hour	3.87	2.92	-0.95
Premiums per hour	17.23	14.43	-2.8

*Note: The control group is all the individuals who did not yet give birth or never did during the sample; the treatment group is the individuals that gave birth once or more during the sample and returned from a period of maternity leave. The numbers are hence the same as in Table 8 above. We have also added Sales, Telephones and Premiums per hour.*

*Table 9* shows a less distinct negative difference than *Table 7*. Hence, when dropping these problematic observations that are gathered within the normal maternity leave period we see a less dramatic difference between the comparison group and the treatment group. This should be expected because the observations gathered in this period that we dropped are deemed less relevant and potentially not representative of the individuals' productivity.

#### 4.4 The Independent Variables

We want to observe whether maternity leave has had any effect on the productivity of the women in the sample. However, we also know that many other things such as ability, education, motivation, age etc. might influence the productivity of certain, if not all, workers. We can, when we have a panel data, root out the *individual-specific fixed effects* and the *time-specific fixed effects* by taking advantage of the fact that we suspect explanatory variables such as education, year born and ability to remain constant over the years.<sup>30</sup> When specifying the model as if each individual has its own constant term, we might be able to better predict the effect of maternity leave on productivity. The downside to this approach is that we will now not be able to say what makes an individual more productive than another on a general basis, that is to say, see the effects of the aforementioned variables on productivity. But this is not the purpose of this paper and has been the purpose of a volume of other articles.

Even though we root out the fixed effects it makes sense to observe whether the groups have any significant differences in key variables such as age and tenure. This is important because we wish to see whether these groups are more or less homogenous or if there are some significant differences between.

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<sup>30</sup> See below for a closer elaboration on the fixed effects methodology and discussion about the methodology of this paper.



**Table 10: t-tests for Difference in Independent Variables**

	<b>t-test for independent variables</b>	
	<b>AGE</b>	<b>TENURE</b>
<i>Mean Mleave = 0 (N = 212)</i>	4.97 (0.14)	97.29 (5.24)
<i>Mean Mleave = 1 (N = 44)</i>	5.25 (0.149)	138 (11.39)
<i>Diff = Mean(0) – Mean(1)</i>	-0.28 (0.315)	-40.71 (4.84)
$H_0: Diff = 0$	NOT REJECTED	REJECTED
$Pr(T > t)$	0.8111	0.9993

*Note: We have rejected the  $H_0$  at the 1%-level in the case of tenure. For age we are not able to say whether the two groups have a systematic difference. We are here comparing those who never had a child with those who did either right before or in the observation period. This is therefore not a direct comparison of the treatment and the comparison group (because some of the individuals appear in both groups). Standard errors in parenthesis.*

On average, a woman that gets pregnant in this particular company seems to be slightly younger than her counterpart that did not have a child during the observation period.<sup>31</sup> However, this difference is not significantly different at any level. The sign of the difference is not surprising, as we know that younger women are more fertile and more likely to have children. It also seems as though women who does not give birth on average work in the company for a shorter period than those who do. This difference is very significant.<sup>32</sup>

A problem for our analysis becomes whether these groups really are comparable or not, especially when we look at tenure. The simple answer to this is yes because almost all the individuals appear in *both* the comparison group and the treatment group. Another argument is that these differences are not necessarily economically large. The women who did not have children worked on average for approximately 40 weeks less than the women who had children in the observation period. But the average number of weeks is likely sufficiently high for both the women with children and the women without children in the sample to say

<sup>31</sup> Age is coded according to:

$$Age\_group = \begin{cases} 1 & \text{if birthyear} \leq 1955 \\ 2 & \text{if birthyear} \in \{1956; 1960\} \\ 3 & \text{if birthyear} \in \{1961; 1965\} \\ 4 & \text{if birthyear} \in \{1966; 1970\} \\ 5 & \text{if birthyear} \in \{1971; 1975\} \\ 6 & \text{if birthyear} \in \{1976; 1980\} \\ 7 & \text{if birthyear} \in \{1981; 1985\} \\ 8 & \text{if birthyear} \in \{1986; 1990\} \end{cases}$$

<sup>32</sup> The difference is significant at the 1%-level against a two-sided  $H_0$ .

something definite about their productivity. It is not certain that an extra 40 weeks for the women that had children would give rise to a higher productivity level. Tabulating mothers indicates that most of them (56.82%) were located in age group 6, while for those who did not give birth it was more evenly spread out over the age groups. Age group 6 was still the one with the highest frequency (25%). Age group 6 is the group where the women were between the ages of 23 and 27 in 2003 when the sample started. The differences make sense intuitively. However, we now know that when comparing these two groups we are looking at one group which is rather age concentrated while the other is more diverse. This could render the comparison a bit futile, because the productivity of the women might be influenced by their cohorts' average productivity. But we do not have any reason to suspect the productivity of the women born between 1976 and 1980 to be any less than the other age groups. In addition; 38 of these women who gave birth are also a part of the comparison group when analyzing them, since they themselves also had a period at work before having a child. Thus this should bring the averages closer together and reduce the potential problems arising from the two groups' different mean ages and tenure.

#### **4.5 Critique of the Data**

There are some arguments against the external validity of this study, the most obvious being that this company is only part of one branch of the economy and do not in itself represent the economy as a whole. Ideally we should have had data from different companies within the same category and different companies in the economy, but in practice this is difficult to obtain. This study will hence not be the ultimate evaluation of productivity after a birth and subsequently a maternity leave period; but it will give an indication to the direction of the effects. Factors such as very generous maternity leave benefits in Norway will also limit the generality of these results. For instance, we might not see the same results as we find here in other types of companies or industries, nor in other countries with a different culture and different institutions than in Norway. So the question of external validity is not fully answered, but the study serves a purpose of being an explanatory study into previously relatively uncharted territories.

In addition we end up removing some observations, namely the observations from women gathered within the normal period of maternity leave. We make the restriction on the data that the observations should not fall within the normal period of maternity leave to make sure we have the correct estimates for the women's productivity. The alternative would be to include

some observations that could be from women just checking in at work or simply logging on to the system to perform administrative duties. We are nevertheless deleting some potential important observations. An indication to the women's dedication and motivation for the work could be if they come back to work earlier after a maternity leave. The return from a period of maternity leave is therefore not necessarily completely exogenous, but can be influenced by factors such as motivation. However, the opportunities for measuring this are difficult.

We also find that *Telephones* as a variable is behaving quite strangely. We see many observations where the number of telephones is reported to be 0. In fact, as *Figure 6* above shows us, almost 15% of the observations have 0 reported answered telephones while some of these observations still have values for sales and the value of sales (*Premiums*). We are thus choosing not to use telephones further as a measure of productivity in our analysis. We hope to see the most important productivity trends from our other dependent variables.

Another point is the complexity of the Norwegian maternity leave scheme. Women have the possibility to take 42 weeks with 100% coverage, 52 weeks with 80% coverage, or up until 2 years with 50% coverage. There is unfortunately no way for us to make any distinctions between these different applications of the scheme in our data. We can also not distinguish the women that are not using all off their maternity leave, are sharing it more generously with their husbands, or are simply leaving to become a homemaker. We have to take this into account when performing the analysis and therefore not draw to blatant conclusions before we have addressed and acknowledged such problems.

Another issue which we have not yet discussed is the possibility of selection issues. The question is whether getting pregnant can be seen as a random assignment into a treatment and a comparison group. Women today have the possibility to plan their pregnancy to a higher degree than before contraceptives became common and abortion became legal. One of the factors that are likely to influence the choice of getting pregnant can be career and work situation. It is also likely that some women might choose to get pregnant at a point in life when they feel their job is unfulfilling or less motivating than earlier. Following Angrist & Pischke (2009: 14), the comparison of expected productivity conditional on maternity leave can be linked to the expected effect of:

$$\begin{aligned}
& E(Y_i|D_i = 1) - E(Y_i|D_i = 0) \\
& = E(Y_{1i}|D_i = 1) - E(Y_{0i}|D_i = 1) + [E(Y_{0i}|D_i = 1) - E(Y_{0i}|D_i = 0)] \quad (0.1)
\end{aligned}$$

Where  $D_i = \{0,1\}$  indicates whether this particular individual receives maternity leave or not. We assume that we can see what might have happened to someone who had a period of maternity leave if that person did not have a period of maternity leave and vice versa. In other words for any individual we study there are two possible outcomes:

$$\text{Possible Outcomes } (Y_i) = \begin{cases} Y_{1i} & \text{if } D_i = 1 \\ Y_{0i} & \text{if } D_i = 0 \end{cases}$$

But we assume we also can observe the counterfactual outcomes:

$$\text{Counterfactual Outcomes } (Y_i) = \begin{cases} Y_{1i} & \text{if } D_i = 0 \\ Y_{0i} & \text{if } D_i = 1 \end{cases}$$

$Y_{1i}$  is the productivity of an individual if she would have a period of maternity leave.  $Y_{0i}$  is the productivity of an individual if she would not have a period of maternity leave.  $E(Y_{1i}|D_i = 0)$  then becomes the expected productivity of an individual that would have a period of maternity leave if she would not have a period of maternity leave. Vice versa  $E(Y_{0i}|D_i = 1)$  is the expected productivity of an individual that would not have a period of maternity leave if she would have a period of maternity leave.

The term  $E(Y_{1i}|D_i = 1) - E(Y_{0i}|D_i = 1)$  from equation (0.1) shows the productivity effect solely linked to maternity leave and is the average causal effect of maternity leave. It is the difference between the expected productivity of those receiving maternity leave  $E(Y_{1i}|D_i = 1)$ , and the expected productivity of those not having a period of maternity leave if they had a period of maternity leave  $E(Y_{0i}|D_i = 1)$ . The difference in productivity status before the incident (maternity leave):  $E(Y_{0i}|D_i = 1) - E(Y_{0i}|D_i = 0)$ , is then the source of selection bias in this model. This term is the difference in expected productivity between those that would be given a maternity leave and those who would not. If we expect that motivation, or the level of productivity, influences the decision to become pregnant and hence take maternity leave we may expect  $E(Y_{0i}|D_i = 1) < E(Y_{0i}|D_i = 0)$  from equation (0.1), making the selection bias negative in our case. We have to keep this in mind for further analyses but we suspect that this effect is not very large. The reason for this is mainly that

even though there are now more opportunities to plan a pregnancy, it might be far-fetched to expect that women become pregnant simply because they are tired or unmotivated at work. We can now move on to explain the model and estimation strategy more thoroughly.

## 5 The Model

The model that will be used to analyze whether maternity leave increase or decrease productivity will be the *differences-in-differences (DID)* model. Known from the field of *effect evaluation*, the DID estimator is comparing observations from a comparison group and a treatment group, and comparing them over time. We can see this as approximating a natural experiment – a so called quasi-experiment. The general thought is that some exogenous incidence occurs which is outside the experimenters control. This incidence, often called the “treatment”, divides the individuals in the sample into a treatment group and a comparison group. Below we shall first discuss how we might proceed to model the effects from such an incidence on a general level. After this we shall narrow it down by discussing how the DID estimator works, and then present some important critiques of this model.

### 5.1 How to Model Effects

The DID model is one of several methods for analyzing and evaluating social programs.<sup>33</sup> The evaluation in itself seeks to estimate the difference in an outcome between the “treated” and “untreated” in the population, after a treatment has occurred. The DID estimator hence makes use of either two distinct time periods (before and after), or an average of the observations before and after the exogenous incident. For instance the “treated” can be a group of people receiving job training by the government or some other institution, while the untreated would be individuals not receiving such training (Heckman et.al, 1999). The theoretical foundations below are built on Heckman et.al (1999), Veerbek (2004; 2008; 2012) and Angrist & Pischke (2009). The goal is to explain and isolate the causal effect from a “treatment” of the individuals. Thus we seek to estimate:

$$E(Y_{1,(t+1)}|X, D = 1) - E(Y_{0,(t+1)}|X, D = 1) \quad (1.1)$$

$E(Y_{1,(t+1)}|X, D = 1)$  is the expected level of, for example, productivity for the individuals or group that has received a treatment if they were given the treatment.  $E(Y_{0,(t+1)}|X, D = 1)$  is the expected level of productivity for the individuals or group that did not receive a treatment if they were given the treatment. The equation (1.1) is then the expected difference in productivity between two different individuals, or a group of individuals, in the state where a

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<sup>33</sup> See for instance Heckman et.al (1999) for more examples.

treatment has occurred.<sup>34</sup> This equation is counterintuitive. How can productivity be estimated for the individuals who were not given treatment *if* they were in fact given the treatment ( $D = 1$ )? We shall use productivity as an example, but the dependent variable might be a number of other factors. The difference in expected outcome is explained by the treatment (indicated by  $D = 1$ ) and some vector of time-varying explanatory variables ( $X$ ). The counterfactual of the situation is thus represented by:

$$E(Y_{0,(t+1)}|X, D = 1) \quad (1.2)$$

We cannot observe a group or a person in two different states at the same time; the fact that those observed are the untreated indicates that they had not received treatment. What we seek to estimate is their expected productivity had they in fact received the treatment. This point is the basis of what we seek to evaluate, and it is what the DID estimator helps us estimate. The reason for observing equation (1.1) is that it does not make sense to *just* compare the after-treatment outcomes of the two groups. This is because they might have some other characteristics rendering them not comparable from the outset (Heckman et.al, 1999). By doing this we would likely find an estimation bias in that the differences might be due to other factors than the treatment which we seek to evaluate. We can more easily estimate:

$$E(Y_{1,(t+1)}|X, D = 1) \quad (1.3)$$

Equation (1.3) is the estimated productivity of the treated in a state of being treated. This can be estimated by using the sample average for this group after the treatment. This may be obtained by either taking the sample average at a specific point in time, or taking the average of the time periods after the treatment.

The main problem thus revolves around how to estimate (1.2) in order to explain (1.1). As we shall see, one of those methods is to make use of the DID estimator.

## 5.2 Introducing the Difference-in-Differences Model

The DID model assumes, according to Heckman et.al (1999), access to longitudinal data on both the treated and the comparison group. It also assumes that the estimated differences between individuals over time in the no-program outcome do not systematically change, i.e. if there was no treatment we should not expect any systematic differences in the dependent

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<sup>34</sup> Subscript  $Y_{1,0}$  indicates whether we talk about those in the state of receiving a treatment ( $Y_1$ ) or those in a state of not having received a treatment ( $Y_0$ ).

variables over time between the two groups. In fact in this case there would not even be two groups, because there has not been any exogenous incident. In the case of an exogenous incident, the groups may have different qualities from the outset rendering the outcomes different. A control for this is using individual fixed effects while estimating. Some individuals might for instance have a much higher initial level of productivity than the others, which would ultimately result in different levels of productivity over time. So the lack of systematic change in the no-program outcome does not mean that the individuals have to be homogenous from the beginning. We use these individual fixed effects to control for heterogeneity among individuals in our own estimation in section 6.

### 5.3 More on the DID model, from Theoretical Framework to Model

We begin by observing a dependent variable  $Y_{it}$  for the entire sample and we propose that the exogenous incident, or the treatment, might have an impact on this outcome. We observe  $i = 1, 2, \dots, N$  individuals over  $t = 1, 2, \dots, T$  time periods. We are assuming that this exogenous incident takes place sometime between period  $t$  and  $t + 1$ .

We begin by introducing a fixed effects model given by:<sup>35</sup>

$$Y_{it} = \alpha_i + \gamma_t + \theta D_{it} + \varepsilon_{it} \quad (1.4)$$

Where  $\alpha_i$  indicates the fixed effects attributed to each individual in the sample,  $\gamma_t$  indicates the fixed effects attributed to each time period, and  $\varepsilon_{it}$  is an error term which is identically and independently distributed and is assumed to take the expected value 0 and constant variance  $\sigma_\varepsilon^2$ . Let us assume that the binary variable  $D$ , indicating treatment or no treatment, is the only explanatory variable. This variable takes the value  $D_{i,t} = 0$  before a specific treatment for each individual, while it for some individuals takes the value  $D_{i,(t+1)} = 1$  after these specific individuals were given the treatment.<sup>36</sup> When estimating, the individual fixed effects are coefficients on dummies for each individual, and the time-specific fixed effects are coefficients on dummies for each time period (Angrist & Pischke, 2009). Hence the fixed effects are in essence being treated as parameters to be estimated.

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<sup>35</sup> How we model the difference-in-differences model is based on Veerbek (2008; 2012) and Angrist & Pischke (2009).

<sup>36</sup> The model can be expanded to include more explanatory time-varying variables.



Estimating deviations from means is algebraically the same as treating the individual effects as parameters to be estimated (Angrist & Pischke, 2009).<sup>37</sup> We may then eliminate these individual fixed effects by first calculating the individual averages over time:

$$\bar{Y}_i = \alpha_i + \bar{\gamma} + \theta \bar{D}_i + \bar{\varepsilon}_i$$

And then subtracting this from (1.4):

$$Y_{i,t} - \bar{Y}_i = (\alpha_i - \alpha_i) + (\gamma_t - \bar{\gamma}) + \theta(D_{i,t} - \bar{D}_i) + (\varepsilon_{i,t} - \bar{\varepsilon}_i) \quad (1.5)$$

Here we have eliminated the individual fixed effects which allow us to make the comparisons needed to evaluate the effect of the treatment. This approach is often termed the *the within-transformation*. We no longer have individual qualities (which are not time-varying) clouding the picture. The negative consequences of this will be discussed below in section 5.4.

To ease the intuition behind the DID estimator, we may eliminate these fixed effects by *first-differencing* the model (1.4). This essentially means that we subtract the time period from before the treatment from the period after:<sup>38</sup>

$$Y_{i,(t+1)} - Y_{i,t} = (\alpha_i - \alpha_i) + (\gamma_{(t+1)} - \gamma_t) + \theta(D_{i,(t+1)} - D_{i,t}) + (\varepsilon_{i,(t+1)} - \varepsilon_{i,t})$$

Or:

$$\Delta Y_{i,(t+1)} = \Delta \gamma_{(t+1)} + \theta \Delta D_{i,(t+1)} + \Delta \varepsilon_{i,(t+1)} \quad (1.6)$$

We see that the individual fixed effects are differentiated out from the equation.<sup>39</sup> They are fixed for each individual and will hence not change over time (this may be: year born, sex, birthplace, etc.). For consistency we must assume that  $E(\Delta D_{i,(t+1)} \Delta \varepsilon_{i,(t+1)}) = 0$  or  $E\{(D_{i,(t+1)} - D_{i,t})(\varepsilon_{i,(t+1)} - \varepsilon_{i,t})\} = 0$ . However, this condition do allow correlation

<sup>37</sup> Deviations from means are the same as estimating each fixed effect in (1.4). The reason for this lies in the regression anatomy formula:  $\widehat{\beta}_1 = \frac{\sum_{i=1}^n \widehat{r}_{11} y_i}{\sum_{i=1}^n \widehat{r}_{11}^2}$  (Wooldridge, 2009) where  $\widehat{r}_{11}$  are the OLS residuals from a

regression of  $x_1$  on  $x_2$ . We may obtain the  $\widehat{\beta}_1$  by regressing our independent variable on all the other independent variables and then regressing the residuals obtained by this regression on our original dependent variable. We are thus estimating  $\widehat{\beta}_1$  in two steps. Deviations from means are the same as estimating fixed effects because the residuals from a regression of a full set of person-dummies on each other in a person-time panel are deviations from person means.

<sup>38</sup> This method assumes two periods. In our analysis we will use more than two periods, and hence the method of subtracting individual means are more appropriate for our model. However, I find it easier to explain the intuition behind the DID estimator by first-differencing but the results are generalizable to the case where subtracting the mean is used.

<sup>39</sup>  $\Delta$  indicates change over time.

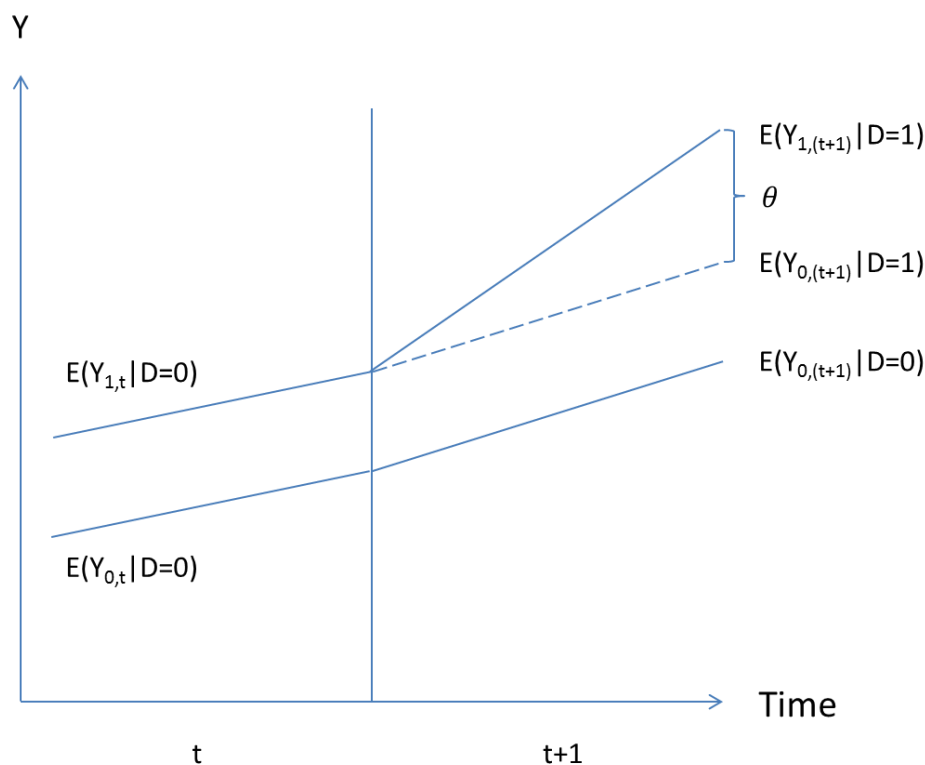
between for instance  $D_{i,(t+1)}$  and  $\varepsilon_{i,(t-1)}$ . It is therefore not as strong as the strict exogeneity condition:  $E(D_{it}\varepsilon_{is}) = 0$  for all  $s, t$ , as mentioned in Veerbek (2008: 360). This means  $\Delta\varepsilon_{i,(t+1)}$  may inhabit some autocorrelation, which should be taken into account. In section 5.4 we will discuss the problem of autocorrelation more. We can now estimate consistently the effect of  $\theta$  with OLS from a regression of  $\Delta Y_{i,(t+1)}$  on  $\Delta D_{i,(t+1)}$ .

The estimate we then get for  $\theta$  is the sample average of  $Y_{i,(t+1)} - Y_{i,t}$  for the treated, minus the sample average of  $Y_{i,(t+1)} - Y_{i,t}$  for the untreated. Let us define  $\Delta\bar{Y}_{(t+1)}^{treated}$  as the average for the treated where  $D_{i,(t+1)} = 1$ , and  $\Delta\bar{Y}_{(t+1)}^{untreated}$  as the average for the untreated where  $D_{i,(t+1)} = 0$ . Then by performing an OLS regression we get:

$$\hat{\theta} = \Delta\bar{Y}_{(t+1)}^{treated} - \Delta\bar{Y}_{(t+1)}^{untreated} = (\bar{Y}_{(t+1)}^{treated} - \bar{Y}_{(t+1)}^{untreated}) - (\bar{Y}_t^{treated} - \bar{Y}_t^{untreated}) \quad (1.7)$$

$\hat{\theta}$  is the difference-in-difference estimator. The difference-in-difference estimator is then *firstly* the difference between the treated and untreated averages and *secondly* the difference over the two time periods.

**Figure 7: Illustration of the How DID Works**



If we use *Figure 7* to illustrate, we may see how the DID estimator works in practice. If we continue to use first-differencing for illustration then, from equation (1.7),  $\bar{Y}_{(t+1)}^{treated}$  will be an estimate on  $E(Y_{1,(t+1)}|D = 1)$  and  $\bar{Y}_{(t+1)}^{untreated}$  will be an estimate for  $E(Y_{0,(t+1)}|D = 0)$ . Furthermore;  $\bar{Y}_t^{treated}$  is an estimate for  $E(Y_{1,t}|D = 0)$  and  $\bar{Y}_t^{untreated}$  is an estimate for  $E(Y_{0,t}|D = 0)$ .

We then see that (1.7):

$$\hat{\theta} = (\bar{Y}_{(t+1)}^{treated} - \bar{Y}_{(t+1)}^{untreated}) - (\bar{Y}_t^{treated} - \bar{Y}_t^{untreated})$$

Is an estimate of:

$$\theta = [E(Y_{1,(t+1)}|D = 1) - E(Y_{0,(t+1)}|D = 0)] - [E(Y_{1,t}|D = 0) - E(Y_{0,t}|D = 0)] \quad (1.8)$$

Observing the figure above,  $\theta$  is exactly the distance between  $E(Y_{1,(t+1)}|D = 1)$  and  $E(Y_{0,(t+1)}|D = 1)$ .<sup>40</sup>  $\hat{\theta}$  then estimates this distance for us. We can also depict this in a table:

**Table 11: Describing the DID method**

	Treated	Untreated	Difference
<b>Productivity before</b>	$\bar{Y}_t^{treated}$	$\bar{Y}_t^{untreated}$	$\bar{Y}_t^{treated} - \bar{Y}_t^{untreated}$
<b>Productivity after</b>	$\bar{Y}_{(t+1)}^{treated}$	$\bar{Y}_{(t+1)}^{untreated}$	$\bar{Y}_{(t+1)}^{treated} - \bar{Y}_{(t+1)}^{untreated}$
<b>Difference</b>	$\bar{Y}_t^{treated} - \bar{Y}_{(t+1)}^{treated}$	$\bar{Y}_t^{untreated} - \bar{Y}_{(t+1)}^{untreated}$	$\hat{\theta}$

This table makes the two dimensions clearer. We take advantage of both a *time-dimension* and a *group-dimension*. This is why it is called the difference (time)-in-difference (group) estimator.

Hence we can, by using the DID estimator, find an estimate for the difference between the state where the treated individuals were given a treatment and the counterfactual state where the untreated individuals were assumed to be treated. This shows us in an intuitive way how the DID estimator can root out the causal effect of the treatment.

We have used the first-differencing approach to show how we can find the DID estimator to ease the intuition behind the model. The only difference between first-differentiation and the fixed effects approach is that the first-difference transformation is employed rather than the

<sup>40</sup> Which, as discussed above (equation 1.1), is what we wish to observe when doing effect evaluation.

within-transformation to eliminate the fixed effects (Veerbek, 2012). We reach the same conclusions as above with equation (1.7) when the within-transformation approach is used as opposed to the first-differencing approach. As explained above, by creating dummies for each individual and time period we are doing algebraically the same as estimating deviations from mean, or employing the within-transformation (Angrist & Pischke, 2009: 223). When creating individual dummies we essentially give each individual their own constant term. The time dummies give each time period a constant term. We can also expand the model to include individual-specific time trends to the list of controls. This allows the individuals in the treatment and the comparison group to follow different individual-specific trends (Angrist & Pischke, 2009). Angrist & Pischke (2009) claim that as a rule, DID estimation with individual-specific trends is “*likely to be more robust and convincing when the pretreatment data establish a clear trend that can be extrapolated into the posttreatment period*” (Angrist & Pischke, 2009: 239).<sup>41</sup>

When estimating the model (1.4) as a regression we specify:

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \hat{\theta} \text{Maternityleave}_{it} + \varepsilon_{it} \quad (1.9)$$

Where  $\mu_i$  is a dummy for each individual, corresponding to the individual fixed effects  $\alpha_i$  in model (1.4). The  $\mu_i$  in essence makes constant terms for each individual, and thus we are treating the individual fixed effects as parameters to be estimated. The time-specific fixed effects ( $\mu_t$ ) works in a similar manner, by creating constant terms for each time period, treating the time-specific fixed effects as parameters to be estimated, and thus controlling for the effect of specific time-periods on productivity. Hence by treating the fixed effects as parameters to be estimated in a regression analysis we may isolate the effect of the treatment on productivity. However, there might still be some time-varying effects rendering the parameter  $\hat{\theta}$  biased. We will look more at how  $\hat{\theta}$  might be biased below.

Following Angrist & Pischke (2009) and Wolfers (2006) we can make our estimation even more robust by introducing the individual-specific time trends. We may allow this trend to take the form of a linear trend, or a quadratic, or some other specification that is appropriate. The specification then becomes:

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<sup>41</sup> In fact Angrist & Pischke (2009) uses state-specific trends in their example, but their claim is valid also for individual-specific trends.

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_i \mu_i * \text{week}_t \right] + \varepsilon_{it}$$

Or with quadratic trends:

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it}$$

Which specification is most appropriate depends on the specific case at hand. The quadratic specification often serves as a control for the possibility that the unobservables can exhibit a more complex dynamic behavior than what may be captured by linear individual-specific trends (Friedberg 1998). Hence the quadratic specification is an expansion to the linear specification. We shall now present the critique of the DID model.

#### 5.4 Critique of the Difference-in-Differences Model

As described above  $\hat{\theta}$  is an estimator of what we presented at the very beginning:

$$E(Y_{1,(t+1)}|X, D = 1) - E(Y_{0,(t+1)}|X, D = 1) \quad (1.1)$$

Whether the condition  $E(\hat{\theta}) = \theta$  is satisfied is a big concern, and what the critique of the DID model is primarily concerned about.

Some general critique of the DID estimator are presented by Bertrand et.al (2002). They claim that most papers using DID focus on serially correlated outcomes, yet fail to acknowledge the bias in the estimated standard errors that such serial correlation introduces.<sup>42</sup> Presenting again:

$$Y_{it} = \alpha_i + \gamma_t + \theta D_{it} + \varepsilon_{it} \quad (1.4)$$

Equation (1.4) is shown by Bertrand et.al. (2002) to grossly understate the true standard errors. The reason for this is essentially that  $E(D_{it}\varepsilon_{is}) \neq 0$  for all  $s, t$ . Productivity this week is quite possibly correlated to the productivity of that individual from last week and the week before that, rendering the standard errors biased, which in turn affects our t-values when estimating. They propose several solutions to this problem. One of which is to collapse the data into 2 periods: before and after, hence ignoring the time-series variation. The other technique is to make an estimate of a variance-covariance matrix which is consistent in the

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<sup>42</sup> Serial correlation and autocorrelation is both used in this paper, but they are the same thing.

presence of any correlation pattern for the individuals over time.<sup>43</sup> The third technique is to use some form of a random inference test to control for the possible autocorrelation in the dependent variable. In section 6.6 we perform some sensitivity analyses to attempt to control for this problem.

Another point of discussion is measurement issues. For example, we might expect the individual fixed effects to be correlated with our treatment indicator. However, this is not really a problem since these individual fixed effects are eliminated as shown in equation (1.5). Hence the estimation approach allows correlation. In some cases one could argue that the individual fixed effects influence the probability of receiving a treatment (Veerbek, 2008: 363). In our case for instance, we might expect the birth year of the observant to influence the probability of pregnancy. Veerbek (2008) argues, with a basis in the elimination process discussed in section 5.3, that this will not cause problems.

Since we eliminate the individual-specific fixed effects in the DID method, we are not worried whether the individuals have different time-constant characteristics which leads them to be self-selected into our treatment group. Such characteristics might for instance be religious affiliation or birth year. The problem for us is if there are some time-varying characteristics that are influencing the choice to have a child and subsequently take a period of maternity leave. But such variables, such as changing motivation, are hard to determine.

We must also discuss the negative effects of removing these individual fixed effects from the equation. For instance, we might expect that birthplace could influence productivity. Schools might for instance be better in the cities; we might observe positive cluster-effects from living in a big city with regards to education and possibly productivity. This effect is not estimated because the individual fixed effects are removed from the equation. Thus, by eliminating the individual fixed effects we lose important information, but without doing this we would not be able to isolate the effect of the treatment.

Another case is the case when there are more N's than T's in the panel. Say for instance we only have 3 time periods, and 100 individuals. Let us also assume that the treatment occurs in period 2. It is then hard to claim with any confidence that one period is enough to estimate

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<sup>43</sup> Bertrand et.al (2002) argues that this is equivalent to using the Newey-West correction (1987) in a context of panel data where one allows for all lags to potentially be important.

specific fixed effects for the individuals. This is not a problem for us as we have observations from a large number of weeks.

With these potential weaknesses in mind we move on to the analyses.

## 6 Analysis

This paper has a stated goal to explore whether maternity leave has a positive or negative effect on productivity if indeed it has any effect. We can therefore propose:

*$H_0$ : Maternity leave yields no effect on productivity*

And:

*$H_1$ : Maternity leave has a significant effect on productivity*

The two-tailed hypothesis are reasonable since the literature, and general reflection on the subject, is not conclusive neither to the point that maternity leave will reduce productivity, nor to the point that maternity leave will increase productivity. We cannot be certain which of the cases are more likely and must therefore be open to both possibilities, although negative effects seem more reasonable. We primarily chose a significance level of 5% to evaluate our results. We begin by analyzing the simplest model without individual specific trends. We then move on to the model with individual-specific linear trends, and then to the model with both individual-specific linear and quadratic trends. After this we will analyze the changing effects from maternity leave on productivity over time. We also compare the effects from maternity leave on the effects from general absence on productivity. Finally we perform some sensitivity analyses to control for problems of autocorrelation and potential extreme values. This chapter is concluded with a comparison of the different models.

### 6.1 Difference-in-Differences by Fixed Effects Estimation

We choose a fixed effect approximation compared to other estimation strategies such as the between-effects estimator and the random effects model. The reason for this is that it might be plausible that the unobserved effects ( $a_i$ ) are correlated with maternity leave.<sup>44</sup> For example, we suspect education and cognitive abilities to be unobserved explanatory variables on productivity. From previous studies the level of education and the number of pregnancies has been linked and there is a suspected correlation (Edwards, 2002). Another reason for choosing Fixed Effects (FE) over Random Effects (RE) is that this is widely considered to be almost always more convincing than RE for policy analysis using quantitative data (Wooldridge,

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<sup>44</sup> From equation (2.1) below.



2009: 493). The argument for random effects on the other hand is that this estimator will produce more efficient results. This is because in general the variance of the random effect estimator will be smaller than the variance of the fixed effects estimator (Verbeek, 2004: 350). Performing the Hausmann test on the simplest model while using *Sales* as the dependent variable<sup>45</sup>:

$$Y_{it} = \alpha_0 + \beta_1 \text{Maternityleave}_{it} + a_i + \varepsilon_{it} \quad (2.1)$$

Yields a result of:  $\text{Prob} > \text{Chi}^2 = 0.9299$ . Hence we fail to reject the  $H_0$  that  $\text{Cov}(\text{Maternityleave}_{it}, a_i) = 0$ . This suggests that perhaps the estimates are sufficiently close so it does not matter which method is used. But considering that the FE estimation is almost always more robust (Wooldridge, 2009), we chose this method rather than using random effects estimation.

We have decided not to use *Telephones* as a dependent variable. The reason for this is that there are significant weaknesses with this variable in the data. For example we find that for 4383 observations the number of telephones picked up equals to 0 even though these same observations have values for *Sales* and *Premiums*.<sup>46</sup> So while on theoretical grounds we would like to include *Telephones*, on empirical grounds we are forced not to. This is regretful as the number of answered telephones is, and should certainly be, a measure of productivity within this company. Fortunately we have good data on both of our other dependent variables and the various adaptations of those referenced above in section 4.2. We also drop *Telephones per hour*.

We start off with the simplest case of regressing maternity leave on our dependent variables, while controlling for both individual-specific and time-specific effects by using a fixed effects approach in order to root out unobserved heterogeneity from omitted variables:

$$Y_{it} = \alpha_0 + \beta_1 \mu_i + \beta_2 \mu_t + \beta_3 \text{Maternityleave}_{it} + \varepsilon_{it} \quad (2.2)$$

This should give us some idea of how maternity leave affects productivity.  $\mu_i$  is a dummy for each individual to control for the individual (fixed-) effects on productivity (such as motivation, ability, education, age etc.).  $\mu_t$  is included to control for time-specific (fixed-)

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<sup>45</sup> We are using the `xtreg` function in STATA, while below we have estimated the fixed effects as parameters within an OLS regression. But this is not very important since (2.1) is used simply as a test to see whether the random effects estimates are similar enough to a fixed effects estimation. We have also not included the time-specific fixed effects rendering the models (2.1) and model (2.2) not directly comparable.

<sup>46</sup> We can see this pattern from *Figure 6* above.

effects such as increasing or decreasing productivity trends in the overall picture of the company or the economy as a whole. In essence we are estimating individual- and time-specific constants to control for all those factors that might influence productivity which we cannot observe.  $Maternityleave_{it}$  is 0 if the individual in a specific time period has not been out in maternity leave, regardless if the individual has a child from previously or not, while it is 1 if the individual has returned from maternity leave to work.<sup>47</sup> The model is very simple, since we cannot observe the “trend differences” which we discussed when presenting the DID approach and individual-specific trends. Performing the regression produces:

**Figure 8: Estimation of Model (2.2)**

	(1)	(2)	(3)	(4)
	Sales	Premiums	Sales/hour	Prem/hour
<i>Mleave</i>	-3.344*** (-6.37)	-89.93*** (-5.87)	-0.0644*** (-3.29)	-1.580*** (-2.65)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>N * T</i>	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.346	0.292	0.262	0.226

t-statistics in parentheses

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

*Note: The results are found using OLS, but with dummies for each individual as well as dummies for each week. Hence we have not used the xtreg function in STATA. The robust command is included to control for heteroskedasticity in the error terms. In STATA we have run the test: “testparm” to test if all the dummies for weeks are jointly equal to 0 after the estimation. This is rejected and hence it is clear that we need to use also time-specific fixed effects in our model.*

It seems like the initial results when looking at maternity leave from *Figure 8* is that the workers returning from such a leave are less productive than other workers. This is on par with some of the previous research suggesting that the depreciation of human capital leads to less productive workers (Rønsen & Sørensen, 1996; Ruhm, 1998; Lai & Masters, 2005). All the coefficients are significant at the 1%-level against a two-tailed hypothesis. The effects are more economically important for the dependent variables not linked to input. For instance, with *Sales per hour* the interpretation of the coefficient is that for every 15.5 hour the individuals that has returned from maternity leave sells 1 less product than the comparison group. This is not a very large drop in productivity. For *Premiums per hour* we have a slightly larger result indicating that the individuals sells for 158 NOK less per hour on average. The average *Premiums per hour* is 1722 NOK in total over the observation period, thus the change is more profound here. But this analysis is quite limited. We might expect that the individuals

<sup>47</sup> It does not become 1 until the 36<sup>th</sup> week after birth as explained above in section 4.3.1. Hence N\*T is here 26138, and not 26697, because some problematic observations are dropped.

are following a specific productivity trend adjusted to them. This trend could for instance be linear or quadratic. We will therefore explore this possibility more below. For *Sales* and *Premiums* the interpretation is that the individuals returning from maternity leave are having approximately 3 less sales per week, and they sell for approximately 9000 NOK less per week. The explanatory power of the model varies from 0.226-0.346 depending on the dependent variable.

## 6.2 Difference-in-Differences with Individual-Specific Linear Time Trends

We also specify individual-specific time trends. When including individual-specific trends we are essentially saying that a flat individual fixed effect may misspecify the underlying productivity behavior imposed by the unobservables. Imposing such constant productivity propensities as in model (2.2) when these propensities are really trending will, according to Friedberg (1998), bias estimates of the constants. The estimated intercepts would in model (2.2) reflect the average of a trend instead of the true intercept which is the individual's initial productivity propensity (Friedberg, 1998). Hence, by introducing such individual-specific trends we are allowing the unobservables of the individuals to each experience a unique trend with their unique intercept. Adding linear individual-specific trends allow for slow-moving trends while the quadratic individual-specific trends allow for a more complex dynamic behavior in the unobservables.<sup>48</sup>

Performing DID then with individual-specific linear trends, following Friedberg's (1998) specification, specified in Wolfers (2006):

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_i \mu_i * \text{week}_t \right] + \varepsilon_{it} \quad (2.3)$$

Yields:

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<sup>48</sup> The use of such individual-specific trends follows Friedberg (1998). See also section 5.3.

**Figure 9: Estimation of Model (2.3)**

	(1)	(2)	(3)	(4)
	Sales	Premiums	Prem/hour	Sales/hour
<i>Mleave</i>	-2.557*** (-2.65)	-91.62*** (-3.27)	-5.468*** (-4.93)	-0.177*** (-4.96)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	YES	YES	YES	YES
<i>Qua.Trend (ind)</i>	NO	NO	NO	NO
<i>N * T</i>	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.406	0.350	0.281	0.322

t-statistics in parentheses  
p<0.1, \*\* p<0.05, \*\*\* p<0.01

*Note: The results are found using OLS with dummies for each individual as well as dummies for each week and not by using the xtreg function in STATA. We have also included individual-specific linear time trends as a control. The robust command is included to control for heteroskedasticity in the error terms. Week 327 is dropped due to colinearity. This does not affect our results, when performing the same analysis without week 327 the results does not change.*

In equation (2.3) we have controlled for individual-specific trends ( $\sum_i \mu_i * week_t$ ) along with time-specific (fixed-) effects ( $\mu_t$ ) and individual (fixed-) effects ( $\mu_i$ ). We observe that all the coefficients from maternity leave on our dependent variables are negative and significant at the 1%-level against a two-tailed hypothesis. We see that the size of the coefficient above is roughly the same as with model (2.2) for *Premiums*. With *Sales* the coefficient are slightly lower here, and barely significant at the 1%-level. The inclusion of the linear individual-specific trends are making the coefficient of maternity leave on *Sales* per hour and *Premiums per hour* approximately 3 times more negative here than above in model (2.2). Now the effects from maternity leave become a drop of one sale every 5.5 hour at work and a drop of 547 NOK every hour in value of sales. Thus it appears that the negative effects from maternity leave is still relevant here, and in fact increases some in our productivity variables linked to input while decreasing some in *Sales*. The explanatory power of the model varies from 0.281-0.406 depending on the dependent variable. Hence this model explains more of the variation in the dependent variables than model (2.2).

### 6.3 Difference-in-Differences with Individual-Specific Linear and Quadratic Time Trends

The explanation for using such a specification is essentially the same as with linear individual-specific trends from the previous section. It serves as a control for the possibility that the unobservables exhibit a more complex dynamic behavior than what is captured by linear individual-specific trends (Friedberg 1998). The quadratic trends then place a stronger restriction on the variation in productivity that can be attributed to maternity leave. Including

quadratic functions might also help to capture decreasing or increasing marginal effects (Wooldridge, 2009: 192). We are essentially allowing the unobservables to potentially follow a parabolic or a U-shaped individual-specific trend, instead of assuming a linear individual-specific trend.

The specification again follows Friedberg's (1998) specification as specified in Wolfers (2006):

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.4)$$

And it yields:

**Figure 10: Estimation of Model (2.4)**

	(1)	(2)	(3)	(4)
	Sales	Premiums	Prem/hour	Sales/hour
<i>Mleave</i>	0.987 (0.66)	-0.961 (-0.02)	-4.215*** (-3.12)	-0.131*** (-2.77)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>Lin. Trend (ind)</i>	YES	YES	YES	YES
<i>Qua. Trend (ind)</i>	YES	YES	YES	YES
<i>N * T</i>	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.436	0.375	0.326	0.366

t-statistics in parentheses

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

*Note: The results are found using OLS with dummies for each individual as well as dummies for each week and not by using the xtreg function in STATA. We have also included individual-specific time trends as a control. The robust command is included to control for heteroskedasticity in the error terms. Individuals 53,443 and 484 are eliminated due to collinearity. The reason for this is that these individuals have 3 or less observations rendering the individual-specific time trends perfectly correlated. Angrist & Pischke (2009) points out that with quadratic individual-specific time trends we need at least 3 periods. Weeks 171 and 327 are omitted due to colinearity. The results again do not change when dropping these weeks and individuals from the analysis.*

When looking at the model with linear *and* quadratic individual-specific trends we observe that the strong significantly negative coefficients from maternity leave on *Sales* and *Premiums* are gone. However, the negative effects from maternity leave on our dependent variables linked to input still remain. The size of these coefficients are slightly lower here than above with model (2.3), but are larger than with model (2.2). They are also significant within our rejection area of the 5% significance level along with the coefficients of maternity leave in model (2.2) and model (2.3). In fact they are both significant at the 1%-level against a two-

tailed hypothesis. So while the actual number of sales and value of sales are uncertain to have been influence by a period of maternity leave, we might say with greater confidence that maternity leave has had a negative effect on *Sales per hour* and *Premiums per hour*. The negative effects from these variables are present in all our models. It is worth noting here that the coefficient of maternity leave on *Sales* is positive, but not significant. The explanatory power of the models varies from 0.326-0.436 depending on the dependent variable. The finding that our quantitative dependent variables do not fall seems somewhat bizarre, as we should perhaps assume that sick leave increases after maternity leave causing the individuals to have fewer registrations at work per week (which naturally would cause a drop in *Sales* and *Premiums* per week). However, evidence from Rieck & Telle (2012) disputes this; sick leave does not seem to increase after maternity leave.<sup>49</sup>

It is also important to take a look at how the effects from maternity leave materialize itself from period to period after the return from maternity leave. This estimation approach below follows Wolfers (2006).

#### 6.4 Changing Effects from Maternity Leave

In this section we wish to observe how the productivity effects of maternity leave are at subsequent periods after the return of the worker. We are thus following Wolfers's (Wolfers, 2006: 1808) specification (2) and model:

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_k \text{Worker has been back at work for } k \text{ weeks after the 36th week}_{it} + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.5)$$

We do this on all our four main dependent variables, while using the specifications (2.2)-(2.4) from above. Hence model (2.5) takes the form of models (2.2)-(2.4) but with the exception that  $\beta_3 \text{Maternityleave}_{it}$  is replaced by

$\beta_k \text{Worker has been back at work for } k \text{ weeks after the 36th week}_{it}$  for each model.

We can do this because the weighted average of the five coefficients below is the coefficients

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<sup>49</sup> See section 3.6. Another feature is that in our data, when observing the mean values for hours worked per week before and after maternity leave, we see that the difference is not quite large (average hours logged on weekly are 29.2 before maternity leave and 28.7 after).

reported above in section 6.1 to 6.3 (Dynarski, 2004: 84). The results for *Sales* and *Premiums* are shown below in *Figure 11*:<sup>50</sup>

**Figure 11: Changing Effects of Maternity Leave on Sales and Premiums, model (2.5)**

	Sales			Premiums		
	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends
Weeks 0-10	-11.14*** (-9.05)	-6.620*** (-4.35)	-1.897 (-1.05)	-285.7*** (-8.15)	-187.5*** (-4.28)	-78.18 (-1.50)
Weeks 11-20	-5.361*** (-4.67)	-2.538* (-1.93)	3.226* (1.89)	-133.2*** (-4.02)	-85.79** (-2.23)	49.75 (1.02)
Weeks 21-36	-2.330*** (-2.81)	-0.295 (-0.27)	6.605*** (4.03)	-62.28*** (-2.67)	-38.13 (-1.23)	125.5*** (2.68)
Weeks 37-52	-1.704* (-1.82)	-1.420 (-1.11)	7.002*** (3.71)	-53.84** (-2.04)	-76.60** (-2.09)	122.5** (2.29)
Week 53 onwards	-1.546** (-2.40)	-1.074 (-0.77)	9.418*** (4.34)	-46.72** (-2.42)	-65.41 (-1.58)	169.6*** (2.71)
<i>Controls</i>						
<i>FE ind.</i>	YES	YES	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	NO	YES	YES	NO	YES	YES
<i>Qua.Trend (ind)</i>	NO	NO	YES	NO	NO	YES
<i>N * T</i>	26138	26138	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.348	0.407	0.437	0.293	0.350	0.376

t-statistics in parentheses

\*p<0.10, \*\*p<0.05, \*\*\*p<0.01

*Note: Again the models are estimated using OLS and are including dummies for each individual and time to control for fixed effects, as well as individual-specific linear and quadratic trends with specifications (2.3)-(2.4). The robust command is included.*

*Figure 11* shows us that the dynamic effects of maternity leave on *Sales* are quite different from model to model. Initially productivity drops strongly, after this the effect is slightly decreasing for the simplest specification (model 2.2). The significance level of our coefficients are at the 1%-level for the first 36 weeks after the return, drops to the 10%-level from week 36-52<sup>nd</sup> after the return, but are then significantly negative at the 5%-level from this point on. When adding individual-specific trends the drop in *Sales* due to maternity leave

<sup>50</sup> We only report results from our regression on *Sales* and *Premiums* here. For *Sales per hour* and *Premiums per hour* please refer to appendix A1.

is initially high and significant at the 1%-level in the first 10 weeks after returning, then slightly decreasing but no longer significant within our rejection area. The model which is including individual-specific linear trends is following roughly the same pattern as the simplest model (2.2), but the negative effects are smaller and are no longer as significant. However, when including the individual-specific quadratic trends the negative significance disappears from even the first 10 weeks and we also see a positive effect of maternity leave from the 11<sup>th</sup> week after return. This positive effect is then highly significant from the 21<sup>st</sup> week and onwards at the 1%-level.

As we see in *Figure 5 Sales* seems to have an initial drop after return but are then slightly increasing again until approximately the 100<sup>th</sup> week after return. From this point on it seems to be slightly decreasing but remaining at a fairly constant level. An intuitive explanation for this is that the women naturally need a period of adjusting to the work again after being away for such a long period. After this period we might assume that the women's productivity increases to previous levels as they again get reaccustomed to work. However, this is not an argument that the model with individual-specific quadratic trends is best since we are discussing the development of the dependent variable over time, and not the development of the unobservables.

For *Premiums* there are negative effects in every period after returning from maternity leave for model (2.2). The negative effect is decreasing for each subsequent period. The effects are first very significant but the significance level drops from the 1%-level in the first 36 weeks to the 5%-level from week 37 and onwards. For model (2.3) the effects are negative but less negative than in model (2.2). The effects do not follow the same pattern of decreasing negative effects. It has a low point from the 21-36<sup>th</sup> week (this effect is not significant) and then the negative effect becomes stronger again from this point on. The results from model (2.3) on *Premiums* are not very significant, except for the first 20 weeks and weeks 37-52. For model (2.4) the effects become positive and significant from the 21<sup>st</sup> week and onwards at the 1%- and 5%-level. The first 10 weeks are negative but not significant. This illustrates what is pointed out above with *Sales*, that it seems plausible that the value of sales initially drops slightly for the period of adjustment and then rises again. What is interesting here is that these coefficients are significantly positive indicating a potential positive effect from maternity leave.



For *Sales per hour* (Figure 15 in appendix A1) it is only the first 20 weeks after return which is significantly negative, after this point in time the effect becomes small and non-significant in model (2.2). For model (2.3) the effects are consistently negative. Most of the results are significant at either the 1%- or the 5%-level. The weeks 21-36 are not significantly negative within our rejection area, and are less negative than the averages above and below it. When including quadratic individual-specific trends the effects are significantly negative for the first 10 weeks at the 1%-level but not significant after this point. Once again the coefficients in this specification are positive from week 21 and onwards but no longer significantly positive.

For *Premiums per hour* the first 20 weeks after return show significantly negative effects of maternity leave in model (2.2). From week 21-36 the effects are no longer significant. When including linear individual-specific trends the negative effects are larger and significant at the 1%- and 5%-level. They are exhibiting the same effects as with model (2.3) above with *Sales per hour*. The effect loses significance when including quadratic individual-specific trends from week 21 and beyond. However, the first 20 weeks show significantly negative effects from maternity leave, week 11-20 are only significant at the 5%-level. In this case the coefficient become positive at the 21-36<sup>th</sup> week after return, but only slightly, and from this point on the coefficients are negative.

We see that the first 10 weeks after return are significantly negative in all our models for the productivity variables linked to input at the 1%-level. The first 10 weeks are also having a significantly negative effect from maternity leave for model (2.2) and model (2.3) for *Premiums* and *Sales*. From this point on the effects become more diverse. We might therefore expect that it is not necessarily a negative effect from maternity leave that materializes itself throughout the continuation of the employees' work-life within this company. It might rather be an adjustment effect from returning from a period of leave. The general image reflected from models (2.2) and (2.3) are that there are negative effects throughout the period after maternity leave but with a varying degree of significance. With model (2.4) the effects are more puzzling and ambiguous showing a drop initially in the productivity variables (although not significant with the variables not linked to input), but from this point on a *positive* effect (the positive effects are not significant in our variables linked to input). We can thus conclude this section that we are not certain whether maternity leave has such a dramatic negative effect that are expected when simply looking at the average of all the periods after treatment in section 6.1 to 6.3. Apart from the first 0-20 weeks after return we can thus not be very conclusive when discussing the effects from maternity leave on productivity.

### 6.4.1 Changing Effects with Dependent Variables on Logarithmic Form

We choose also to specify a logarithmic form of the dependent variables. We do this to control for potential extreme values in our dynamic analyses above:

$$\begin{aligned} \ln(Y_{it}) = & \alpha_0 + \beta_1\mu_i + \beta_2\mu_t \\ & + \beta_k \text{Worker has been back at work for } k \text{ weeks after the 42nd week}_{it} \\ & + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.6) \end{aligned}$$

Observing the figures, the effects do not change dramatically.<sup>51</sup> For model (2.2) for log (*Sales*) we see that the negative effects of maternity leave becomes more significant when using logarithms.<sup>52</sup> The negative effects of the first 20 weeks with model (2.3) is also more significant than above, and the negative effects from week 37 and onwards are also significantly negative at the 5%-level. When specifying log (*Sales*) the first 10 weeks in the model with individual-specific quadratic trends is also significantly negative at the 1%-level, this is not the case with model (2.4) in *Figure 11*. The positive effects from week 21 and onwards are still present and significant when using the logarithm.

We see that as with *Sales*, all the weeks post maternity leave are significantly negative when taking log (*Premiums*) with model (2.2). The first 20 weeks after maternity leave is also more significantly negative in model (2.3) when taking the logarithms then in *Figure 11*. For model (2.4) the same change occurs as with log (*Sales*), the first 10 weeks are significantly negative, while the weeks 21 and onwards are significantly positive.

For *Sales per hour* we see that the negative effects are more significant when using logarithms in model (2.2).<sup>53</sup> The negative effects from model (2.3) are following roughly the same pattern when using logarithms compared to when not. The first 10 weeks after maternity leave is significantly negative when observing model (2.4) when using logarithms. Weeks 21 and onwards are significantly positive at the 5%- and the 10%-level. The weeks 21-36 & 53 and onwards are significantly positive within our rejection area.

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<sup>51</sup> The results from the models with changing effects where the dependent variable is specified as the natural logarithm of *Sales*, *Premiums*, *Sales per hour* and *Premiums per hour* is reported in Appendix A2.

<sup>52</sup> *Figure 16*.

<sup>53</sup> *Figure 17*.

For *Premiums per hour* the negative effects in model (2.2) are also more significant when using logarithms, although not after week 52. The pattern in model (2.3) changes little when introducing logarithmic dependent variables compared to *Figure 15*. The negative effects of the first 20 weeks are also significantly negative in model (2.4) when using logarithms. Week 53 and onwards are now significantly positive.

Thus, some of the significance levels changes when using logarithms. In general the negative coefficients become more significant when using a logarithmic specification. However, the overall picture does not change dramatically. Perhaps most interestingly the positive effects from week 21 and onwards are still highly present and significant in model (2.4) for *Sales* and *Premiums* when using logarithms. To some extent our coefficients also become significantly positive for *Sales per hour* and *Premiums per hour* in the weeks after the 21<sup>st</sup> week after return for model (2.4) as well. Thus the positive effect in section 6.4 cannot be explained by potential outliers.

## 6.5 Maternity Leave vs. General Absence

In this section we will compare the results we found above in sections 6.1-6.3 with results we get by observing how long term absence affects productivity. We follow the same modeling and procedure as above and use the difference-in-difference approach to observe the effects. We have used the same sample as when looking at maternity leave. Now the treatment group is the observations from individuals who have been away from work for a whole consecutive 10 weeks. The comparison group becomes the individuals which did not have such a long period of absence from work, and the observations from individuals before they had such a long leave of absence from their work. We should suspect declining productivity in accordance with the results from Markussen (2012) mentioned above in section 3.5. It is important to note that the determinants of sick leave are not assumed to be determined in the same exogenous way as maternity leave; this will of course render our results less robust. The models we use are essentially:

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Returned}_{it} + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.7)$$

Where  $\text{Returned}_{it}$  is a dummy indicating whether the individual has returned from a period of 10 weeks absence or not. When performing the analysis we observe the results from

regressions in the same way as section 6.1-6.3 above. Hence we add  $\sum_i \mu_i * week_t$  when specifying individual-specific linear trends and add  $\sum_i \mu_i * week_t + \sum_i \mu_i * week_t^2$  when specifying both linear and quadratic individual-specific trends. The reason why we are not specifying that the individuals should have a total period of 42 weeks absence, as we do above with maternity leave, is that very few individuals have such a long period of absence due to any other reasons than maternity leave. In order to ensure enough observations we are forced to reduce the required amount of weeks for acceptance into our treatment group to 10 weeks. This will of course render the situations not directly comparable. However the weaknesses of such an approach, we do this to compare general absence with maternity leave to observe whether there are some major differences between those two cases, and to see whether maternity leave might have similarities effects to other absences.

The results from the regressions on model (2.7) are depicted below.<sup>54</sup>

**Figure 12: The Effect of Absence on Sales per hour and Premiums per hour, model (2.7)**

	<i>Basic Model (2.2)</i>		<i>Individual-specific linear trends (2.3)</i>		<i>Individual-specific linear and quadratic trends (2.4)</i>	
	<i>Sales per hour</i>	<i>Premiums per hour</i>	<i>Sales per hour</i>	<i>Premiums per hour</i>	<i>Sales per hour</i>	<i>Premiums per hour</i>
<i>Absence</i>	-0.0720*** (-3.90)	-1.976*** (-3.86)	-0.121*** (-4.27)	-3.080*** (-4.04)	-0.224*** (-6.78)	-5.797*** (-6.50)
<i>Controls</i>						
<i>FE ind</i>	YES	YES	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	NO	NO	YES	YES	YES	YES
<i>Qua.Trend (ind)</i>	NO	NO	NO	NO	YES	YES
<i>N * T</i>	26697	26697	26697	26697	26697	26697
<i>Adjusted R<sup>2</sup></i>	0.261	0.224	0.323	0.281	0.368	0.328

t-statistics in parentheses

\*P<0.10, \*\*P<0.05, \*\*\*P<0.01

*Note: As with model (2.3) in section 6.2 week 327 is dropped from the sample. As with model (2.4) individuals 53,443 and 484 are eliminated due to colinearity also here. Weeks 327 and 171 are also dropped from model (2.4) due to colinearity. The results do not change when dropping these observations and weeks from the analysis altogether. Robust is included.*

<sup>54</sup> The results for *Sales* and *Premiums* are reported in Appendix A3.

Observing the results from the regressions on the effect of absence on productivity we see that when linking output to input, as is done with *Sales per hour* and *Premiums per hour*, the estimated coefficients are quite similar here to the ones we found in section 6.1-6.3. Compared to model (2.2) from section 6.1 the effect of a continuous absence of 10 weeks is slightly larger than the effect from a period of maternity leave. When compared to model (2.3) from section 6.2 the results show that the estimated effect of an absence is comparatively smaller than when we look at the effect from maternity leave. When comparing to model (2.4) from section 6.3 above we observe that the effects from a period of 10 weeks absence are stronger than the effects of maternity leave on *Sales per hour* and *Premiums per hour*. All estimated coefficients are significant at the 1%-level.

When observing *Sales* and *Premiums* we no longer see the same effects as above in section 6.1-6.3.<sup>55</sup> In fact only the coefficients from model (2.2) specified on (2.7) are significantly negative at the 5%-level. The effect of a continuous absence for 10 weeks shows positive effects on *Sales* and *Premiums* when specifying individual-specific linear trends, and when specifying individual-specific linear and quadratic trends. But these effects are not significant.

We thus see a comparable situation when looking at the productivity variables which are linked to input, but not when we observe the productivity variables which are not. This supports a view that the individuals become less productive per hour due to long-term absence.

## 6.6 Sensitivity Analysis

We perform some sensitivity analyses here. We do this to check our results for potential errors, mainly from serial correlation which are often a problem in panel data research (Bertrand et.al 2002), but also to control for potential outliers/extreme values for section 6.1-6.3 as we have already done with our analyses on changing effects. As explained in section 5.4, serial correlation leads to underestimation of the standard errors which in turn might cause larger t-values and hence we might find significance where there is none. We have already controlled some for the reliability of our results by using the robust command. This ameliorates some of the potential heteroskedasticity in our results. But it is also necessary to use a method to explore the reliability of our estimates when it comes to autocorrelation.

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<sup>55</sup> See Figure 18 in Appendix A3.

Before we do this we will take a look at the residuals from the estimation of the simplest model on *Sales*:

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \varepsilon_{it} \quad (2.2)$$

The residuals and their respected lags are shown below in a correlation-matrix:

**Table 12: Correlation Matrix of Residuals and their lags from model 2.2 (with Sales)**

	<i>Residuals</i>	<i>1 lag</i>	<i>2 lags</i>	<i>3 lags</i>	<i>4 lags</i>	<i>5 lags</i>	<i>6 lags</i>	<i>7 lags</i>	<i>8 lags</i>
<i>Residuals</i>	1.0000								
<i>1 lag</i>	0.3213	1.0000							
<i>2 lags</i>	0.2333	0.3213	1.0000						
<i>3 lags</i>	0.1839	0.2333	0.3213	1.0000					
<i>4 lags</i>	0.1608	0.1839	0.2333	0.3213	1.0000				
<i>5 lags</i>	0.1500	0.1608	0.1839	0.2333	0.3213	1.0000			
<i>6 lags</i>	0.1323	0.1500	0.1608	0.1839	0.2333	0.3213	1.0000		
<i>7 lags</i>	0.1209	0.1323	0.1500	0.1608	0.1839	0.2333	0.3213	1.0000	
<i>8 lags</i>	0.1183	0.1209	0.1323	0.1500	0.1608	0.1839	0.2333	0.3213	1.0000

Observing the data it seems that the residuals are correlated to a relatively high degree, but are behaving as expected in the sense that this correlation recedes over time.<sup>56</sup> Since the residuals indicate differences from the estimated function value this might indeed indicate high autocorrelation in our true population standard errors. Below we therefore try an adjustment to our standard errors.

### 6.6.1 Newey-West Correction

As mentioned above in section 5, one major problem with using the DID model is the potential autocorrelation in the standard errors. One way of trying to cope with this problem is to use the Newey-West correction to our, potentially, serially correlated standard errors.<sup>57</sup> The thought behind the Newey-West correction is that while there might be some serial correlation in the standard errors, we would also expect the correlation to fall over time. That is:

$$\text{Cov}(\varepsilon_t \varepsilon_s) \rightarrow 0 \text{ when } (t - s) \rightarrow \infty \quad (A1)$$

Newey-West is, by introducing lags, using this implication. It estimates a variance-covariance matrix, which is consistent in the presence of any correlation pattern within states over time (Bertrand et.al 2002). It uses the assumption A1, which assumes that the correlation between the residuals approaches zero as the distance between the observations approaches infinity

<sup>56</sup> See assumption (A1) below for a description of how the correlation is expected to behave.

<sup>57</sup> Bertrand et.al (2002) advocates this as a possible method in their article.

(Petersen, 2009). Petersen (2009) reviews 207 papers in the field of financial economics and finds that seven percent of these papers use the Newey-West correction to correct for potential serial correlation. The amount of lags to include in the analysis is a matter of the *economics* of the problem. We see from *Table 12* that the residuals are correlated up to at least 8 lags. Though, the correlation tends to fall over time and it seems to be moving towards 0.10 at the 8<sup>th</sup> lag. Because of this we choose 8 lags, after this point we might expect the correlation to drop more slowly. 8 lags are also often used in the literature (Petersen, 2009).

Performing the Newey-West correction on the basic estimated model:

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \varepsilon_{it} \quad (2.2)$$

Gives us the following estimates:

**Figure 13: Sensitivity Analysis 1, Newey-West Correction on model (2.2)**

	(1)	(2)	(3)	(4)
	Sales	Premiums	Sales/hour	Prem/hour
<i>Mleave</i>	-3.344*** (-4.10)	-89.93*** (-3.96)	-0.0644** (-2.24)	-1.580* (-1.93)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	NO	NO	NO	NO
<i>Qua.Trend (ind)</i>	NO	NO	NO	NO
<i>N * T</i>	26138	26138	26138	26138

t-statistics in parentheses

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

*Note: The standard errors are suspected to be undervalued when no correction for autocorrelation is performed (Bertrand et.al 2002), hence the t-values are suspected to be lower when this correction is made which this figure shows. Defining how many lags that should be included when performing Newey-West is a matter of discretion. We have lagged the variables 8 weeks, because we might expect that after this point the autocorrelation is slowing down according to assumption A1, and because this is what has been done in previous analysis (Petersen, 2009).*

We observe that the  $\beta_3$ 's are the same above as in *Figure 8*, as they are expected to be. However, the t-values are smaller than above.<sup>58</sup> This might not be crucial to our analysis since even when we make the corrections for serial correlation the t-statistics are large in model (2.2). But we observe that the coefficients of maternity leave on *Sales per hour* and *Premiums per hour* lose some significance. They drop from the 1%-level above in *Figure 8* to the 5%- and 10%-level, respectively, against the two-tailed hypothesis. We see that Newey-West

<sup>58</sup>For instance is  $t_{Sales}^{Newey-West} = -4.10$  while  $t_{Sales}^{OLS} = -6.37$ . With the other variables the new t-values are also lower when using Newey-West.

forces the t-values down by around  $1/3^{\text{rd}}$ , yet they are still very significant indicating that there might be negative productivity effects from maternity leave.<sup>59</sup> When performing the Newey-West specification on the standard errors with model (2.3) we see that the negative coefficient on *Sales* is no longer significant within our rejection area. The negative coefficient on *Premiums* are no longer significant at the 1%-level but are significant at the 5%-level. For *Sales per hour* and *Premiums per hour* we still see significantly negative coefficients at the 1%-level. When observing the results from a Newey-West specification on the standard errors of model (2.4) we see that maternity leave has no significant effect on *Premiums* and *Sales* as with section 6.3 above. The previously significantly negative effects on *Sales per hour* are no longer significantly negative within our rejection area. The negative coefficient from maternity leave on *Premiums per hour* is still significant at the 5%-level. Hence much of the significance is lost when controlling for autocorrelation for model (2.4).

### 6.6.2 Logarithmic Specifications

To control for potential extreme values above in sections 6.1-6.3 we can introduce a logarithmic form. The logarithmic form makes the estimates less vulnerable to the effect of outlying observations on the dependent or independent variables (Wooldridge, 2009: 191). The result of taking the logarithm is that the distribution of the dependent variables approximates more closely a normal distribution; it can mitigate problems of skewed distributions in strictly positive variables as we have here (Wooldridge, 2009: 191). It especially makes sense to take the logarithm when we are discussing positive monetary values such as dollars, or in our case kroners, as with *Premiums* (Wooldridge, 2009). This is because such values tend to be distributed within a large interval. In our case we can estimate:

$$\ln(Y_{it}) = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \varepsilon_{it} \quad (2.8)$$

The results from the estimation are presented below:

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<sup>59</sup> Results from performing Newey-West on our other models (2.2)-(2.4) are reported in appendix A4.



**Figure 14: DID Based on logarithmic model (2.8)**

	(1)	(2)	(3)	(4)
	ln (Sales)	ln (Premiums)	ln (Sales/Hour)	ln (Premiums/Hour)
<i>Mleave</i>	-0.436*** (-9.53)	-0.476*** (-8.64)	-0.357*** (-7.64)	-0.397*** (-7.11)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
N	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.328	0.293	0.302	0.276

t-statistics in parentheses

\* p&lt;0.1, \*\* p&lt;0.05, \*\*\* p&lt;0.01

*Note: Analysis is again done by OLS while specifying dummies for individuals and time.*

We observe that the coefficients are still negative indicating a negative effect of maternity leave on productivity. We also observe that the t-values are high, rendering all our dependent variables significantly negative at the 1%-level. Introducing such a logarithmic specification does not seem to alter our results from section 6.1; actually it seems to create larger t-values. The results seems to suggest that women returning from maternity leave sells for 43.6% less, compared to before maternity leave and compared to women that had no period of maternity leave. The value of their sales is 47.6% lower than the comparison group. The individuals who have experienced a period of maternity leave sell for 35.7% less per hour and the value of their sales are 39.7% lower compared to the comparison group.

When looking at the other models with linear and quadratic individual-specific trends we observe the similar tendency with the coefficients.<sup>60</sup> Observing *Figure 21* we see that when including linear individual-specific trends the women that had a period of maternity leave have 44.4% less sales than the comparison group, they sell for 53.1% less, their sales per hour is 62.6% less, and they sell for 53.8% less per hour than the comparison group. All of these coefficients are significant at the 1%-level. When including the quadratic individual-specific trend as well in *Figure 22* the individuals have 14.6% less sales after a maternity leave compared to the comparison group and they sell for 27.8% less. However, none of these two effects on the dependent variables are significant within our rejection area. In the same model the individuals in the treatment group seems to have 52.2% less sales per hour than the

<sup>60</sup> Observe Appendix A5 for the results from this estimation.

comparison group and sell for 38.9% less. Both of these last two coefficients are significant at the 1%-level.

Thus, we see that when observing the coefficients of maternity leave on our two dependent variables where output is linked to input (*Sales per hour* and *Premiums per hour*), we find significantly negative results in all our model specifications at the 5%-level or below. These effects also seem economically large and are within the range of 35.7%-62.6% less *Sales per hour* after a period of maternity leave, and within the range of 38.9%-53.8% less for *Premiums per hour*.

## 6.7 Comparisons

We see from section 6.1 that the results from a difference-in-difference estimation of maternity leave on productivity show a clear and significantly negative effect from maternity leave. We can thus reject the  $H_0$  in this case. In essence this means that on average women that returned from maternity leave sells fewer products, and less valuable products, than women who did not have a period of maternity leave or did not yet have a period of maternity leave. But as already mentioned, the ratio of sales and value of sales to hours worked does not fall very much. The adjusted  $R^2$ 's are within the interval of 0.226-0.346 indicating there is still much of the variation in productivity which is not explained by maternity leave. Such factors might for instance be health and motivation.

When introducing the individual-specific linear trends to control for slow-moving trends in the effect of the unobservables on productivity we see that the results become more profound, especially with our productivity variables linked to input. The coefficient on *Sales per hour* fall by almost three times the size from section 6.1 to section 6.2 rendering the negative effect of maternity leave on *Sales per hour* stronger here than before. *Premiums per hour* fall by almost four times the size of the equivalent coefficient in model (2.2). This result follows Friedberg's (1998) to a certain degree, she finds stronger and more significant results when specifying such individual-specific trends as controls. The adjusted  $R^2$ 's are within the interval of 0.281-0.406 indicating that such a model explains more of the variation in productivity than model (2.2).

When controlling for individual-specific quadratic trends the significantly negative coefficients on *Sales* and *Premiums* disappear. However, the significantly negative effects of *Premiums per hour* and *Sales per hour* still remain, and are below the level of model (2.3) but

above the level of model (2.2). The adjusted  $R^2$ 's are within the interval of 0.326-0.436 indicating even higher explanatory power of the model.

Which of the models are more correct? All of them indicate a significantly negative effect from maternity leave on productivity for the variables linked to input, within the range of 0.0644-0.177 for *Sales per hour* and 1.580-5.468 for *Premiums per hour*. Two out of three models also indicate a significantly negative effect from maternity leave on our productivity variables not linked to input. According to Angrist & Pischke (2009), a rule for when difference-in-difference estimation is more robust and convincing when using individual-specific trends is that the pretreatment data should establish a clear trend that can be extrapolated into the post-treatment period. We have shown that while before birth the individuals follow a somewhat negative linear trend, after the return from maternity leave they are following a somewhat parabolic quadratic trend.<sup>61</sup> It is therefore not necessarily clear that the trend shown by the pretreatment data can be extrapolated into the post-treatment period. But in whatever model we chose, we still have significantly negative estimated coefficients from maternity leave on the productivity variables linked to input. This is suggesting that we can say with some certainty that on average over time maternity leave is affecting productivity negatively.

We are likely experiencing something similar to what Wolfers (2006) found when discussing what effects shift in divorce regimes has on divorce in the short and the long run. He explains that some pent up demand for divorces are spiking the rate immediately after an implementation of reform to divorce laws, but then gradually the rate falls back again to some steady state. It is plausible to assume, especially when observing *Figure 5* and *Figure 23* that something like this is also happening here. A period of adjustments after a maternity leave cause a drop in productivity before it eventually moves back again towards some steady state. The question is then if the productivity again reaches its former levels, or if there is a new steady state at a lower point than earlier. Wolfers (2006) critiques Friedberg (1998) for using a dummy variable turning one after the exogenous event, and being 0 before, because any dynamics in the period after is efficiently washed out and only the average before and after effects remain. Sections 6.1 to 6.3 have essentially followed Friedberg (1998), we now need to move on to section 6.4 which tries to explain these dynamics with Wolfers's (2006) specification.

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<sup>61</sup> See *Figure 5* and *Figure 23* (Appendix B)

We observe that model (2.2) is showing significantly negative coefficients for almost all the weeks after return from maternity leave for our productivity variables not linked to input. However, the models with individual-specific linear trends and with individual-specific linear and quadratic trends are not.<sup>62</sup> Only the first 10 weeks consistently shows a significantly negative effect when specifying individual-specific linear trends. In fact, when specifying both individual-specific linear and quadratic trends, the initial negative relationship between maternity leave and productivity changes sign and eventually turns positive after the 21<sup>st</sup> week.

For our productivity variables linked to input the negative effects after the 21<sup>st</sup> week is no longer significantly negative for the basic model.<sup>63</sup> The model with individual-specific linear trends, and the model with individual-specific linear and quadratic trends, now shows significantly negative results for many of the weeks after maternity leave. The effect from the first 10 weeks after return is consistently, and significantly, negative.

The results from section 6.4 and 6.4.1 suggests together that we can be rather confident that at least the first 10 weeks after return have a negative effect on productivity for all our dependent variables. 22 of 24 coefficients are significantly negative at the 1%-level. In addition, 16 of 24 coefficients on the 11<sup>th</sup> to the 20<sup>th</sup> weeks after return show significantly negative results at the 5%-level or below. After this point the results become less coherent and we shall refrain from concluding too much for the weeks after this.

We also have to bear in mind that all of the results is dependent on how we design maternity leave. We could for example have shortened the period an employee is expected to be on maternity leave, or expanded it, and there would be good arguments for both cases. In essence we have to make a distinction somewhere and that is what we have done here. This problem also follows us into the discussion of the effect on productivity from general long term absence vs. maternity leave.

When looking at general absence compared to maternity leave we see very significant negative results from being away for 10 consecutive weeks for our variables linked to input.<sup>64</sup> However, for the variables not linked to input the results are not significant for models (2.3)

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<sup>62</sup> See Figure 11.

<sup>63</sup> See Figure 15.

<sup>64</sup> See Figure 12.

and (2.4) and the sign of the coefficients are not consistent.<sup>65</sup> Compared to our results from section 6.1-6.3; both general absence for 10 consecutive weeks and maternity leave show consistently negative coefficients on *Sales per hour* and *Premiums per hour*. For *Premiums* and *Sales* the negative effects from both cases are less certain. We also see that the negative coefficients from maternity leave and absence are quite similar. For the basic model:  $\beta_{Sales/Hour}^{Mleave,2.2} = -0.0644^{***}$  and  $\beta_{Sales/Hour}^{Absence,2.2} = -0.0720^{***}$ , for specification (2.3):  $\beta_{Sales/Hour}^{Mleave,2.3} = -0.177^{***}$  and  $\beta_{Sales/Hour}^{Absence,2.3} = -0.121^{***}$ , and for specification (2.4):  $\beta_{Sales/Hour}^{Mleave,2.4} = -0.131^{***}$  and  $\beta_{Sales/Hour}^{Absence,2.4} = -0.224^{***}$ . The biggest difference is that while the negative coefficient from absence seems to become more negative with the inclusion of more controls, the negative coefficients from maternity leave becomes more negative from model (2.2) to model (2.3) and then slightly less negative again when including individual-specific quadratic trends (2.4). The negative coefficients on *Premiums per hour* are very similar to *Sales per hour*. It seems that absence for 10 consecutive weeks have much of the same negative effect on productivity as maternity leave has. But we must consider that since sick leave is not necessarily determined exogenously the validity of our results is not as strong as with maternity leave.

We can argue that the productivity variables linking input to output show higher validity than the productivity variables not linked to input. A reason for this is that a worker might be present for less than the entire week, yet still have observations from this week. For instance, in Norway workers are allowed 10 days off work for reasons such as a sick child if the child is below the age of 12. It might also be plausible to expect the sick leave to increase after maternity leave perhaps because, as mentioned in section 3.1, of the adverse health effects from pregnancy. We do not find much evidence for this in our data, the average hours logged on to the system per week is just 0.5 lower after maternity leave. But it is always more reasonable to connect the output of the worker to their input (Mark, 1982), and in our opinion these variables are more valid and better for measuring productivity.

The sensitivity analysis reduces the estimated standard errors such that *Premiums per hour* are no longer significantly negative at our chosen level for the basic model (2.2). *Sales per hour*, as well as *Sales* and *Premiums*, are still significantly negative. For model (2.3), the coefficient on *Sales* is no longer significantly negative at our chosen level but the coefficients on *Sales*

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<sup>65</sup> See Figure 18 in Appendix A3.

*per hour* and *Premiums per hour* are significantly negative at the 1%-level. The coefficient on *Premiums* remain significant at the 5%-level. For model (2.4), controlling for autocorrelation in our estimates drops the significance level of all our coefficients. Only the negative coefficient on *Premiums per hour* remains significant at the 5%-level. Our results here are sensitive to the number of lags we include; it is possible that if we included more lags the significance levels might have dropped also from the models (2.2)-(2.3).

We also estimate the models while using random effects to compare with the results from sections 6.1-6.3. The results from random effects estimation is not differing very much from our results from the fixed effects estimation.<sup>66</sup> This is an argument for the reliability of our results and supports our results above; but it could also be an argument for using RE instead of FE due to RE's generally more efficient results.

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<sup>66</sup> The results from the estimation of random effects are not presented here but are available from the author upon request.

## 7 Conclusion

The main results from this investigation of the impact of maternity leave on productivity are as follows:

- Our results indicate that maternity leave has a negative effect on productivity upon return. The DID estimates from sections 6.1-6.3 all show significantly negative effects on especially the variables linked to input. Some of the significance disappears when controlling for autocorrelation, especially when using individual-specific quadratic trends.
- The regressions depicting the changing effects of maternity leave on productivity are indicating that this negative effect can largely be attributed to the first 0-20 weeks after the estimated return from maternity leave.
- When controlling for potential outliers with a logarithmic specification of our dependent variables the results do not change markedly, neither do the results change markedly when specifying a random effects model. This indicates that the pattern is robust when controlling for different estimation techniques.

What we can conclude from this is that maternity leave is likely to have a negative impact on productivity. However, we are not sure if this is because of adverse effects from the maternity leave itself or simply the period of absence. We present results indicating that general absence has much of the same effects as maternity leave have on productivity. We also have indications that the first 20 weeks upon return are the weeks where productivity is at the lowest point after maternity leave. This tells us that perhaps the negative productivity effects can be attributed to “relearning” much of the work after a long period of absence. It also tells us that we are not sure whether there is a long term negative effect from maternity leave. We must also be careful when interpreting the results from the different time periods after maternity leave due to its complexity as a scheme, and the many different applications it allows. Our results are found when making some assumptions to when the individuals leave and return which can easily be critiqued.

In addition, when controlling for autocorrelation some of the previously significant results disappear – especially with our model including individual-specific quadratic trends. This

might indicate that our negative relationship is not as strong and significant as previously expected.

In many ways this paper has been an exploration into previously uncharted territories. In previous research maternity leave has been assumed to behave as any other leave from work, and the predictions have been that it will depreciate human capital. Our findings go a long way in supporting such an assumption. We cannot find any evidence that maternity leave is a milder form of leave, led by exogenous events, which ameliorates any depreciation of human capital from absence. In fact, maternity leave seems to lead to lower productivity, at least initially, and has many of the same features as 10 weeks absence from work. However, what we believe is that maternity leave in itself is perhaps not the reason for the productivity loss, but rather a factor ameliorating the adverse health effects from birth. In essence we believe that the loss of productivity could have been greater had there not been any kind of maternity leave available for women, and that the adverse health effects from giving birth is the one of the main negative effects on productivity.

It is important to note that even if maternity leave has a negative effect upon productivity it is, in my opinion, not an argument against maternity leave as a governmental or private scheme. As previous research suggests, a period of maternity leave seems to be ameliorating the adverse health effects caused by pregnancy and birth. Previous research also suggests that women and families benefit from this more preferred life/work choice. It is thus reasonable to assume that if there were no allocated time for maternity leave, the negative consequences of birth on productivity might have been even worse. The maternity leave as a governmental scheme in Norway is not heavily debated, and there is general consensus about its existence.

A cross-country comparison of different maternity leave schemes and their effect on women's productivity is an ideal area for further research. It is plausible to assume that birth will have largely the same effect on women regardless of their country of origin. Thus comparing for example the U.S. and Norway, where the length of maternity leave are quite different, would be an interesting field of study. Making comparisons between men and women would also be interesting. In Norway men are not the main benefactor of parental leave. However, in countries such as Iceland, where the parents divide the parental leave so that each parent has at least 1/3<sup>rd</sup> of the leave, a comparison between the effects from parental leave on productivity for men and for women would be interesting. It must be mentioned that Norway



in comparison to many other countries has very generous maternity benefits; it should therefore be a focus of further research to look at other countries. In addition, other types of companies should be studied, perhaps companies where physical labor is more common, in order to expand our knowledge of how maternity leave influence productivity.

Other estimation strategies such as the before-after estimator (comparing the person with himself/herself), or the cross-section estimator (comparing participants and non-participants at a certain point in time), could also give more insight on how maternity leave affects productivity. In addition there are other estimation strategies such as the random effects model, or a combination of random effects and fixed effects, which could produce even more insight. We must also mention that important explanatory variables such as changing psychological and physical health status, changing motivational status, changing wage status, and changing working conditions are left out from our analyses. Gaining access to such potential explanatory variables would definitely help us increase our understanding of how maternity leave affects productivity.

Maternity leave is a different kind of absence from work than other absences. As mentioned in the introduction, it can be assumed to be less prone to endogeneity than for example sick leave. Even today, when women have the possibility to protect themselves against unwanted pregnancies, it can be difficult to argue that women become pregnant simply because they are not motivated at work. With sick leave it can be argued that low motivation can be one of the factors determining the employee's absence. For instance, we often hear tales of being "burned out". Another factor with maternity leave is that it is not an absence designed solely for the individual's well-being and to ameliorate health effects. A main argument for the scheme is that it can improve family relations and the development of children. The absence does not then necessarily assume that the worker is at worse health. This is simply one of the many arguments for the absence compared to sick leave where this is the main argument. Another factor is that maternity leave is not as prone to signaling effects as Markussen (2012) claims sick leave is.

The motivation for looking at maternity leave has thus been that since this is such a different kind of leave than other absences, it has been interesting to look at how the effects from maternity leave on productivity are empirically. Our research has suggested that in fact it behaves much like other leaves are expected to behave, which implies that perhaps previous

assumptions on how human capital will develop have been more or less correct. However, much research remains on this subject and to determine its true effect one should compare different estimation strategies, observe different companies and countries, compare men and women and include more explanatory variables. Only then can we learn more about the true effect of maternity leave on productivity.

**Appendix A1: Changing Effects on Sales per hour and Premiums per hour**

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_k \text{Worker has been back at work for } k \text{ weeks after the 36th week}_{it}$$

$$+ \left[ \sum_i \mu_i * week_t + \sum_i \mu_i * week_t^2 \right] + \varepsilon_{it} \quad (2.5)$$

**Figure 15: Changing Effects of Maternity Leave on SPH and PPH, model (2.5)**

	SPH			PPH		
	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends
Weeks 0-10	-0.383*** (-9.60)	-0.330*** (-6.65)	-0.241*** (-4.18)	-9.690*** (-8.60)	-9.101*** (-6.20)	-7.146*** (-4.30)
Weeks 11-20	-0.185*** (-5.09)	-0.196*** (-4.45)	-0.0963* (-1.76)	-4.573*** (-4.33)	-5.816*** (-4.34)	-3.633** (-2.29)
Weeks 21-36	-0.0237 (-0.84)	-0.0712* (-1.73)	0.0578 (1.07)	-0.526 (-0.66)	-2.887** (-2.27)	0.0626 (0.04)
Weeks 37-52	-0.0297 (-0.95)	-0.145*** (-2.95)	0.0225 (0.36)	-0.942 (-1.04)	-5.144*** (-3.37)	-1.320 (-0.72)
Week 53 onwards	0.0271 (1.09)	-0.124** (-2.15)	0.0681 (0.92)	0.774 (0.98)	-4.450** (-2.41)	-0.696 (-0.31)
<i>Controls</i>						
<i>FE ind.</i>	YES	YES	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	NO	YES	YES	NO	YES	YES
<i>Qua.Trend (ind)</i>	NO	NO	YES	NO	NO	YES
<i>N * T</i>	26138	26138	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.264	0.323	0.366	0.227	0.350	0.426

t-statistics in parentheses

\*p&lt;0.1, \*\*p&lt;0.05, \*\*\*p&lt;0.01

Note: The models are estimated using OLS and including dummies for each individual and week to control for fixed effects, as well as individual-specific linear and quadratic trends with specifications (2.3)-(2.4). The robust command is included.

**Appendix A2: Logarithmic Specification on Changing Effects**

$$\ln(Y_{it}) = \alpha_0 + \beta_1 \mu_i + \beta_2 \mu_t + \beta_k \text{Worker has been back at work for } k \text{ weeks after the 42nd week}_{it}$$

$$+ \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.6)$$

**Figure 16: Changing Effects of Maternity Leave on log (Sales) and log (Premiums), model (2.6)**

	Log (Sales)			Log (Premiums)		
	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends
Weeks 0-10	-1.375*** (-14.36)	-0.975*** (-8.34)	-0.562*** (-3.88)	-1.538*** (-12.09)	-1.124*** (-7.28)	-0.724*** (-3.83)
Weeks 11-20	-0.682*** (-6.94)	-0.468*** (-4.33)	0.0722 (0.51)	-0.807*** (-6.62)	-0.584*** (-4.25)	-0.0338 (-0.19)
Weeks 21-36	-0.290*** (-4.03)	-0.157* (-1.67)	0.471*** (3.44)	-0.330*** (-3.76)	-0.196* (-1.74)	0.461*** (2.71)
Weeks 37-52	-0.242*** (-2.94)	-0.238** (-2.15)	0.552*** (3.59)	-0.257*** (-2.81)	-0.263** (-2.03)	0.573*** (3.06)
Week 53 onwards	-0.233*** (-4.28)	-0.245** (-2.08)	0.665*** (3.88)	-0.216*** (-3.47)	-0.243* (-1.71)	0.739*** (3.48)
<i>Controls</i>						
<i>FE ind.</i>	YES	YES	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES	YES	YES
<i>Lin. Trend (ind)</i>	NO	YES	YES	NO	YES	YES
<i>Qua. Trend (ind)</i>	NO	NO	YES	NO	NO	YES
<i>N * T</i>	26138	26138	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.332	0.424	0.466	0.298	0.394	0.435

t-statistics in parentheses

\*p&lt;0.10, \*\*p&lt;0.05, \*\*\*p&lt;0.01

Note: The models are estimated using OLS and including dummies for each individual and week to control for fixed effects, as well as individual-specific linear and quadratic trends with specifications (2.3)-(2.4). The robust command is included.

**Figure 17: Changing Effects of Maternity Leave on log (SPH) and log (PPH), model (2.6)**

	Log (SPH)			Log (PPH)		
	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends	(2.2) Basic Model	(2.3) Individual- Specific Linear Trends	(2.4) Individual- Specific Linear and Quadratic Trends
Weeks 0-10	-1.404*** (-14.15)	-1.140*** (-9.71)	-0.844*** (-5.77)	-1.567*** (-12.05)	-1.288*** (-8.34)	-1.006*** (-5.28)
Weeks 11-20	-0.714*** (-7.26)	-0.641*** (-6.00)	-0.253* (-1.81)	-0.839*** (-6.89)	-0.756*** (-5.57)	-0.359** (-2.03)
Weeks 21-36	-0.151** (-2.04)	-0.152* (-1.65)	0.314** (2.31)	-0.182** (-2.10)	-0.192* (-1.74)	0.303* (1.79)
Weeks 37-52	-0.181** (-2.21)	-0.323*** (-2.93)	0.289* (1.88)	-0.196** (-2.16)	-0.348*** (-2.70)	0.310* (1.66)
Week 53 onwards	-0.108** (-2.03)	-0.328*** (-2.78)	0.371** (2.18)	-0.100 (-1.60)	-0.325** (-2.31)	0.445** (2.10)
<i>Controls</i>						
<i>FE ind.</i>	YES	YES	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	NO	YES	YES	NO	YES	YES
<i>Qua.Trend (ind)</i>	NO	NO	YES	NO	NO	YES
<i>N * T</i>	26138	26138	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.308	0.405	0.449	0.308	0.382	0.424

t-statistics in parentheses

\*p&lt;0.10, \*\*p&lt;0.05, \*\*\*p&lt;0.01

Note: The models are estimated using OLS and including dummies for each individual and week to control for fixed effects, as well as individual-specific linear and quadratic trends with specifications (2.3)-(2.4). The robust command is included.

**Appendix A3: The Effect of Absence on Sales and Premiums**

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Returned}_{it} + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.7)$$

**Figure 18: The Effect of Absence on Sales and Premiums, model (2.7)**

	<i>Basic Model (2.2)</i>		<i>Individual-specific linear trends (2.3)</i>		<i>Individual-specific linear and quadratic trends (2.4)</i>	
	Sales	Premiums	Sales	Premiums	Sales	Premiums
<i>Absence</i>	-1.180** (-2.27)	-36.12** (-2.55)	1.153 (1.47)	28.01 (1.35)	0.747 (1.46)	17.44 (1.62)
<i>Controls</i>						
<i>FE ind</i>	YES	YES	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	NO	NO	YES	YES	YES	YES
<i>Qua.Trend (ind)</i>	NO	NO	NO	NO	YES	YES
<i>N * T</i>	26697	26697	26697	26697	26697	26697
<i>Adjusted R<sup>2</sup></i>	0.335	0.282	0.402	0.346	0.435	0.375

t-statistics in parentheses

\*P&lt;0.10, \*\*P&lt;0.05, \*\*\*P&lt;0.01

*Note: As with model (2.3) in section 6.2 week 327 is dropped from the sample. As with model (2.4) individuals 53,443 and 484 are eliminated due to colinearity also here. Weeks 327 and 171 are also dropped from model (2.4) due to colinearity here. The results do not change when dropping these observations and weeks from the analysis altogether. Robust is included to control for heteroskedasticity.*

**Appendix A4: Newey-West Corrections on (2.3)-(2.4)****Figure 19: Sensitivity Analysis 2, Newey-West on Model (2.3)**

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_i \mu_i * \text{week}_t \right] + \varepsilon_{it} \quad (2.3)$$

	(1)	(2)	(3)	(4)
	Sales	Premiums	SPH	PPH
<i>Mleave</i>	-2.557* (-1.84)	-91.62** (-2.38)	-0.177*** (-3.84)	-5.468*** (-4.08)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>Lin. Trend (ind)</i>	YES	YES	YES	YES
<i>Qua. Trend (ind)</i>	NO	NO	NO	NO
<i>N * T</i>	26138	26138	26138	26138

t-statistics in parentheses

\* p &lt; 0.10, \*\* p &lt; 0.05, \*\*\* p &lt; 0.01

Note: Week 327 dropped as in section 6.2. This does not alter the results. Standard errors are calculated with the Newey-West estimation.

**Figure 20: Sensitivity Analysis 3, Newey-West on Model (2.4)**

$$Y_{it} = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.4)$$

	(1)	(2)	(3)	(4)
	Sales	Premiums	SPH	PPH
<i>Mleave</i>	0.987 (0.42)	-0.961 (-0.02)	-0.131* (-1.92)	-4.215** (-2.25)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>Lin. Trend (ind)</i>	YES	YES	YES	YES
<i>Qua. Trend (ind)</i>	YES	YES	YES	YES
<i>N * T</i>	26138	26138	26138	26138

t-statistics in parentheses

\* p &lt; 0.10, \*\* p &lt; 0.05, \*\*\* p &lt; 0.01

Note: Individuals 53,443 and 484 are eliminated due to colinearity. Weeks 327 and 171 are also dropped. This does not alter the results. Standard errors are calculated with the Newey-West estimation.

**Appendix A5: Logarithmic Specifications on (2.2)-(2.4)****Figure 21: DID Based on logarithmic model (2.9)**

$$\ln(Y_{it}) = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_t \mu_i * \text{week}_t \right] + \varepsilon_{it} \quad (2.9)$$

	(1)	(2)	(3)	(4)
	ln(Sales)	ln(Premiums)	ln(PPH)	ln(SPH)
<i>Mleave</i>	-0.444*** (-5.38)	-0.531*** (-5.14)	-0.538*** (-6.56)	-0.626*** (-6.08)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	YES	YES	YES	YES
<i>Qua.Trend (ind)</i>	NO	NO	NO	NO
<i>N * T</i>	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.423	0.392	0.403	0.379

t-statistics in parentheses

p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Note: The results are found using OLS with dummies for each individual as well as dummies for each week and not by using the xtreg function in STATA. We have also included linear individual time trends to control for different development over time across individuals. The robust command is included to control for heteroskedasticity in the error terms.

**Figure 22: DID Based on logarithmic model (2.10)**

$$\ln(Y_{it}) = \alpha_0 + \beta_1\mu_i + \beta_2\mu_t + \beta_3\text{Maternityleave}_{it} + \left[ \sum_i \mu_i * \text{week}_t + \sum_i \mu_i * \text{week}_t^2 \right] + \varepsilon_{it} \quad (2.10)$$

	(1)	(2)	(3)	(4)
	ln(Sales)	ln(Premiums)	ln(PPH)	ln(SPH)
<i>Mleave</i>	-0.146 (-1.13)	-0.278* (-1.71)	-0.389*** (-3.03)	-0.522*** (-3.20)
<i>FE ind.</i>	YES	YES	YES	YES
<i>FE weeks</i>	YES	YES	YES	YES
<i>Lin.Trend (ind)</i>	YES	YES	YES	YES
<i>Qua.Trend (ind)</i>	YES	YES	YES	YES
<i>N * T</i>	26138	26138	26138	26138
<i>Adjusted R<sup>2</sup></i>	0.464	0.432	0.446	0.421

t-statistics in parentheses

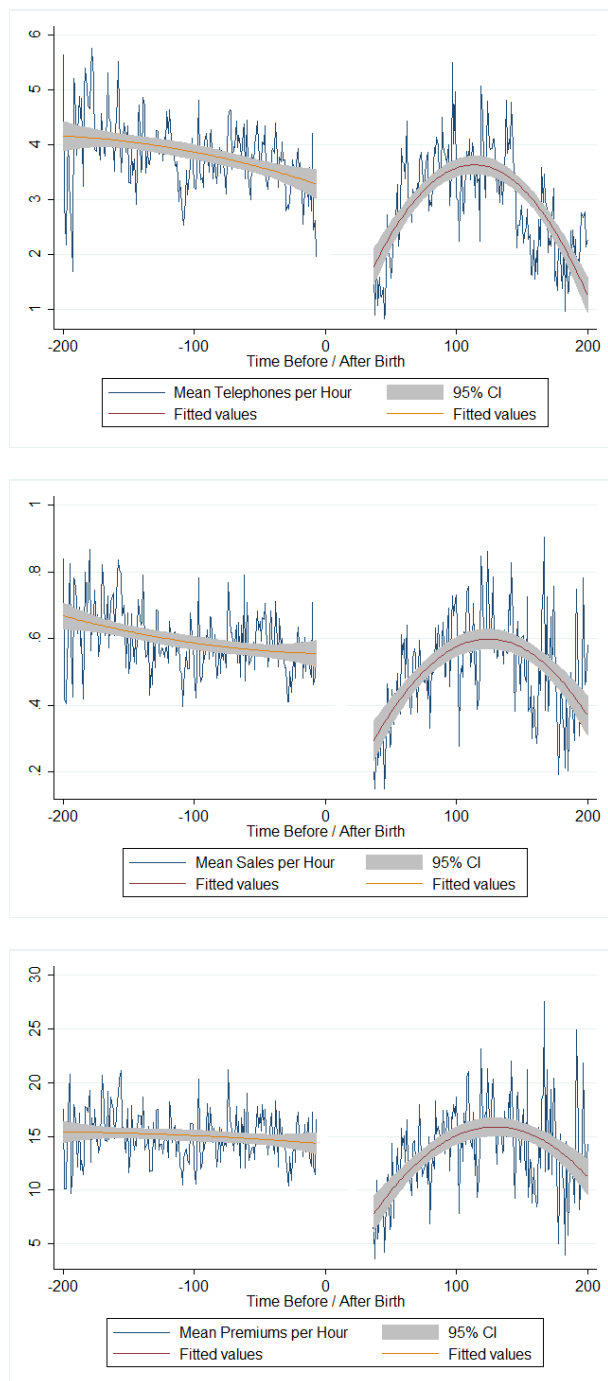
p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Note: The results are found using OLS with dummies for each individual as well as dummies for each week and not by using the xtreg function in STATA. We have also included linear and quadratic individual time trends to control for different development over time across individuals. The robust command is included to control for heteroskedasticity in the error terms.



## Appendix B1: The Before/After for Sales per hour, Telephones per hour & Premiums per hour

**Figure 23: The Before/After Sales per hour, Telephones per hour & Premiums per hour**



*Note: The interval is discontinuous because the values between the 7<sup>th</sup> week before birth and the 37<sup>th</sup> week after birth are dropped. This follows from the discussion of maternity leave laws in chapter 2.3. The trend is also limited to between the 200<sup>th</sup> week before birth and the 7<sup>th</sup> week before birth, and the 37<sup>th</sup> week after birth and the 200<sup>th</sup> week after birth, due to few observations after this point. The time variable is not the same as in Figure 4, but a constructed time measurement (in weeks) for illustration of the weeks spent at work before and after a birth, and subsequently a period of maternity leave.*

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