ANALYZING MATERNAL EMPLOYMENT AND CHILD CARE QUALITY

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Analyse van Arbeidsmarktparticipatie van Moeders en de Kwaliteit van de Kinderopvang
(met een samenvatting in het Nederlands)

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To my uncle Ismail Erbay

Acknowledgements

You will notice that my name is printed in large letters on the cover, which might give the impression that I wrote this thesis all alone. Of course, that is far from the truth. There are a number of people who contributed to the quality and helped with the completion of this thesis, and I am happy to have this opportunity to thank at least some of them.

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Chapter 1

Introduction

The shift of women from the household to the labor market during the 20th century has fundamentally transformed both the labor force that they moved into and the household tasks they left behind. Basic outputs of women in households such as food, child care and clothing, became domains of the markets that employed women. Issues such as gender wage gaps and work-life balance became topics of both academic and policy discussion. Perhaps the most dramatic impact of the increase in female labor force participation is observed during early years of motherhood. Outsourcing child care to the market has become a necessity for families to maintain dual incomes rather than a luxury enjoyed by the few in pursuit of more leisure time.

Employment during motherhood is analyzed not only by economists but also by researchers in developmental psychology and sociology. If we limit ourselves purely to the economics literature, there is interest in two major outcomes: mothers' employment and child development. Policies aimed at either outcome are usually justified by the proposed economic benefits in the face of aging populations. Child development is linked with future life outcomes in employment and education while female labor supply expands the tax base. Beyond economic benefits that are reflected in the GDP, both outcomes have non-pecuniary welfare benefits such as promoting gender equality and child welfare.

My contributions revolve around both mothers' employment and child development. The first topic of interest is how mothers' employment is affected by modern child care services and parental leave entitlements. There is already an extensive literature on the effects of modern social policies such as child care services and parental leave entitlements (Ruhm, 1998; Blau and Currie, 2006). A related second topic is how child care quality is produced and influenced by policy measures. Positive findings from the UK and USA of targeted intervention programmes such as STAR, Perry Preschool and Sure Start do not prove that large scale investments can also have large effects on child development, but they do give an indication of the potential returns to child care policies focused on improving quality (Melhuish et al., 2008; Heckman et al., 2010; Chetty et al., 2011).

This thesis begins by evaluating the literature linking child care prices to labor supply and attempting to explain the differences in the findings. The previous studies focus mostly on the empirical link between prices and labor supply. The next chapter covers parental leave, where researchers tend to use micro level data of mothers to identify the effects of taking up leave on rates of return to employment and wages (Ondrich et al., 1996; Lalive and Zweimüller, 2009). I provide an aggregate level analysis in terms of employment rates, working hours, occupational segregation and wages, which extends and updates the previous studies that focus on employment and wages (Ruhm, 1998).

Child care quality has recently received increasing attention from researchers and policymakers (Bennett and Tayler, 2006). The change in terminology among policymakers and academics from child care to early childhood education and care (ECEC) seems to underline the transition from viewing child care as a service that facilitates parents employment to one that plays a role in human capital formation. Education in later years have long been studied with regard to how privatization of schools and spending in education affect educational quality (Hanushek, 1994; West and Woessmann, 2010). Since there is a general trend towards privatization of welfare state functions including child care services across OECD countries, the same questions analyzed for schooling are becoming more relevant also for the child care sector. I extend the literature on schooling quality to the early childhood years by analyzing how child care quality is affected by competition among centers and by public spending. In the final chapter, I go back to the literature on child care and labor supply and extend it by analyzing how quality influences female labor supply.

Apart from the literature review in chapter 2, the methods of analysis are empirical. Identification strategies include both structural modeling and exploiting policy changes. Chapter 3 uses aggregate level data from OECD countries in general while the remaining chapters use micro level data from the Netherlands. In the next section I discuss the state of female employment during motherhood and child care services across OECD countries and discuss how quality is being measured. The final section of the introduction provides a general overview of the chapters' research questions and methodology.

1.1 Trends in Female employment and the measurement of quality

Figure 1.1 shows the labor force participation rates of women in the EU-15, OECD and the Netherlands over the period 1970-2010. The participation rate has gone up by around 15% points among OECD countries. The rise in female labor force participation in the Netherlands is particularly large since it starts very low and increases quickly to levels exceeding OECD and EU averages. Despite high participation rates among women across OECD countries, figure 1.2 shows that employment during motherhood is unsurprisingly low in most countries. The more relevant point to highlight in figure 1.2 is that the gap between female employment and maternal employment differs across countries. This seems to suggest that country specific child care policies and institutions have a large role to play in determining women's employment decisions and vice versa.

The generosity and provision method of child care services and parental leave entitlements vary considerably between OECD countries. Traditionally, child care has been viewed as a function of the welfare state. Nevertheless, similar to service sectors such as schooling and health care, there is a mix of provision methods among OECD countries ranging from public supply and financing to private market provision and parental fees (Kamerman, 2000). Figure 1.3 shows that child care spending varies considerably even among high income OECD countries. Parental leave policies also differ as shown by the take up rates in figure 1.4. Entitlements range from rights to year long, fully funded leave periods in Sweden to only 16 weeks of paid maternity leave and 3 months of unpaid parental leave in the Netherlands. In addition to cross-country differences, child care and parental leave policies tend to be dynamic over time. From relatively short leave periods exclusive to women in the 1970s, many Nordic countries' parental leave policies have evolved into long, generous leave periods with specific rights for fathers. As recent as 2009, the German parental leave system was overhauled with shorter leave periods with more generous benefits. Child care systems and financing are similarly fluid, with the Netherlands privatizing the child care system in 2005 and Germany beginning a major expansion of child care

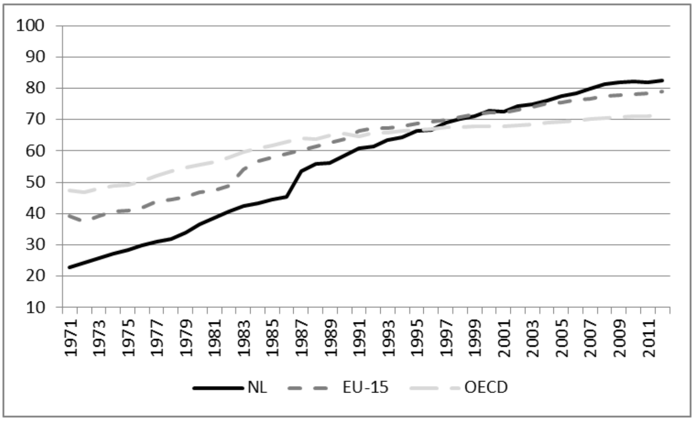


Figure 1.1: Female Labor Force Participation 1970-2010
Source: OECD Family Database

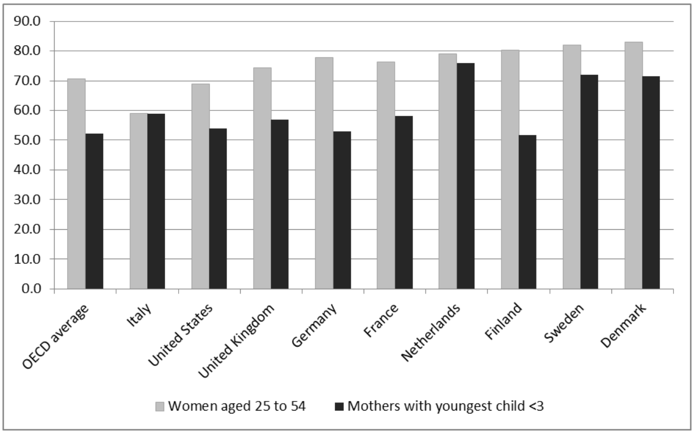


Figure 1.2: Female Employment and Motherhood 2009
Source: OECD Family Database

services in 2008. Given the fluidity of child care and parental leave policies over time and across countries, policymaking requires evaluations of their effects on both mothers' employment and children's experiences.

The increase in female labor force participation seen in figure 1.1 has translated into large scale child care services in many OECD countries. Figure 1.5 shows that more than 60% of children under 3 in Denmark and the Netherlands are enrolled in

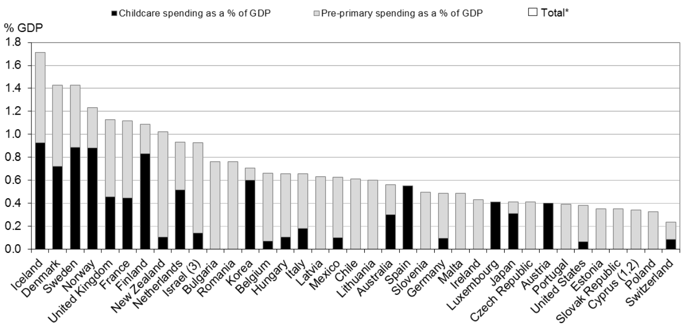


Figure 1.3: Child Care Spending in the OECD
Source: OECD Family Database

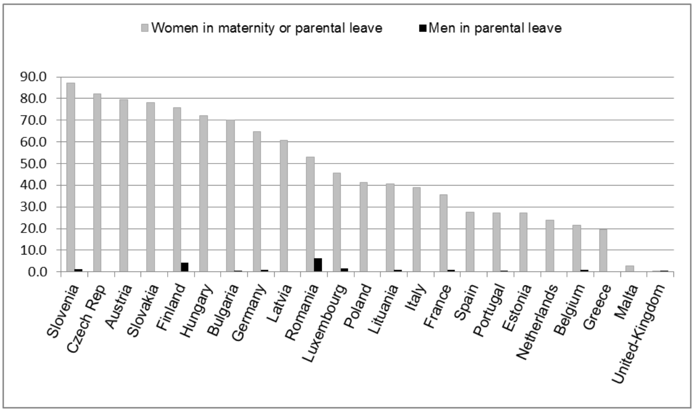


Figure 1.4: Parental Leave Take-up Rates for Parents with a Child under 1
Source: OECD Family Database

child care and the rates are much higher across the OECD countries in ages between 3 and 5. Given the high enrollment rates in child care services and pre-school programmes, the quality of child care can have dramatic effects on entire generations.

The differences across OECD countries in the methods of child care provision and financing can result in quality differences. Unlike prices, for which indicators are widely available, measuring child care quality is difficult. Blau (1997) makes the useful distinction between structural indicators such as staff to child ratios or staff qualifications as inputs and the quality of children's educational experience and child-caregiver interactions as outputs of quality production in child care centers. The latter is defined as process quality by developmental psychologists and are measured using assessments based on classroom observations. Unlike attending formal child care where there is mixed evidence regarding effects on child development, higher process quality is generally positively related to child development (Burchinal et al., 2000; Vandell et al., 2010).

Due to the cost of measuring child care quality, most surveys including it are country specific. In this thesis, a recent survey of Dutch child care centers and parents, Pre-Cool, is used to analyze the production of child care quality. The Pre-Cool survey is similar in structure to the well-known longitudinal panel of the American National Institute of Child Health and Development (NICHD) called the Study of Early Child Care and Youth Development (SECCYD). The Dutch child care system has undergone considerable transformation since the Child Care Act of 2005, which introduced a private market for the daycare services with concurrent subsidies for parents' child care expenditures. The policy trend between 2005 and 2008 was towards increasing subsidies especially for high income parents, which led to the current situation where over 300,000 of households with children receive child care subsidies. As of 2012, the subsidies became less generous for middle income and high income families and were especially reduced for second sibling in child care. Figure 1.5 shows that across OECD countries in 2010, the Netherlands had one of the largest proportions of children under 3 in child care.

Other than the large size of its child care sector, the Netherlands has has three distinct advantages for the analysis of child care quality and its effects. First, the introduction of the private daycare market in 2005 allows for a study of how market forces, primarily competition, affects child care quality. Second, the recent changes in the subsidies paid to parents allow for natural experiments that exploit these changes.

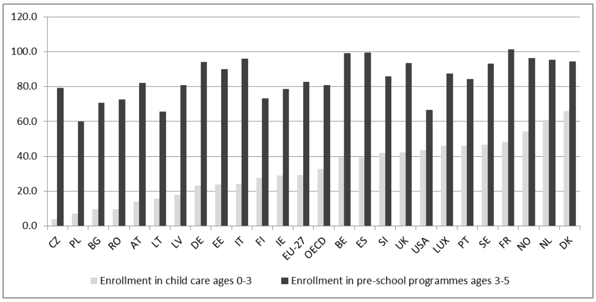


Figure 1.5: Child care enrollment rates 2010
Source: OECD Family Database

Third, Dutch playgroups, which are pre-schools targeted to children aged 2.5 and 4 and provide part-time child care for single income families, form a potential control group for the effects from market forces or subsidies on daycare centers since they are funded by municipalities.

1.2 Outline and overview

Any economic study on child care or female labor force participation can trace its lineage to the theoretical work by Becker (1960) on household behavior and to the econometric foundations of Heckman (1974) in estimating female labor supply. While the starting point for the present thesis is the economic literature on female labor supply, the latter part of the thesis introduces and analyzes child care quality as defined by developmental psychologists. Within economics, the study of child care quality and child development in general is more recent than the study of labor supply. While effects on mothers' employment from child care services is analyzed within the labor supply literature, effects on child development are closer to the human capital literature. If early childhood and consequently child care quality has large effects on future life outcomes, study of pre-primary education becomes a natural extension of the human capital literature in economics that largely focuses on post primary schooling (Heckman, 2006).

The thesis begins with two chapters that directly study mothers' employment. Chapter 2 reviews and analyzes, using meta-analysis techniques, the extensive literature on child care prices and labor supply. The chapter shows that methodological improvements have been made over time, especially with the introduction of studies using natural experiments and flexible multinomial choice models. However, even more than the methodological differences, the context and timing of the studies may explain the variation found in the estimated elasticity of employment with regards to child care prices. Over time, child care prices have become less important in women's decision to work. In countries like Sweden where female employment rates are similar to that of male employment, Lundin et al. (2008) have found that further decreases in already low prices do not seem to dramatically affect employment behavior. A similar result is found in Norway using a natural experiment by Havnes and Mogstad (2011a). This is in contrast to earlier studies in the United States where large employment elasticities were found (Ribar, 1995; Connelly and Kimmel, 2003a). Using regression techniques from the meta-analysis literature, the chapter attempts to determine whether there are clear patterns to where and when child care prices have a large effect on employment.

The other main public policy besides subsidizing child care has been paid or unpaid parental leave arrangements. Chapter 3 updates the results of earlier studies, particularly that of Ruhm (1998), by using a difference-in-differences to estimate the effects of changes in parental leave legislation on female labor market outcomes. Using aggregate OECD data from 1970 to 2008, a dataset is generated that traces the changes in parental leave legislation during that period for 16 European countries. Male labor market outcomes serve as the main control group to estimate the effects of changes in parental leave legislation on female employment, wages and occupations. We use ILO wage data for manufacturing and financial sectors as proxies to study both low and high skill wages.

The following three chapters of the thesis analyze the production of child care quality and the effects of quality on labor supply. The primary dataset in all three studies is Pre-Cool, a longitudinal survey of child care centers and parents from the Netherlands. Chapters 4 and 5 of the thesis focus on the production of quality itself. Blau (1997) provides early evidence on how center characteristics such as size or age affect child care quality. One possible framework to analyze the production of quality is to define it as an outcome of variables from three sets. The first set of variables are the previously studied center characteristics such as staff-to-child ratios, teacher qualifications and center size. The second set is the market in which the center operates. The final set of variables consists of national policies and legislation that affect the behavior and decisions of both the centers and the parents. In chapter 4, I study the second level by analyzing the effects of market competition. In chapter 5, the level of national policies are studied through an analysis of subsidies.

Analogous to studies in schooling, and other sectors such as manufacturing or health care, chapter 4 considers how competition affects child care quality. Similar to other service sectors, the effects of competition on quality and prices are not theoretically straightforward due to market imperfections and information asymmetries. I use the number of centers in Dutch neighborhoods as the competition variable and instrument it using number of schools and births from previous years to estimate its effect on child care quality. Child care quality is measured within the Pre-Cool survey using process quality measures introduced in the child development literature. The chapter analyzes the potential effects of private sector competition on the quality of both the private daycare centers and the municipality funded playgroups.

Chapter 5 introduces the role of public financing of child care services. Specifically, we analyze the effect of a subsidy reduction in 2012 on Dutch daycare centers' quality. Previous studies of such effects relied generally on reduced-form, cross-sectional evidence (Johnson et al., 2012). The timing of the Pre-Cool survey before and after the subsidy reduction provides an interesting opportunity to estimate potentially causal effects using quasi-experimental methods. The playgroups that are funded through the municipalities are not affected by the subsidy cut and are used as the control group. Using both linear and non-linear difference-in-difference estimators, I estimate both the main and quantile effects.

Chapter 6 returns to the labor market to analyze the effects of child care quality on female labor supply. Quality is introduced into the existing structural econometric models found in Ribar (1995) and Tekin (2007) as a variable similar to child care prices. Reduced form equations are used to predict wages, child care prices and child care quality for the women in the Pre-Cool sample. These predicted values are included in a random coefficient multinomial logit model that estimates their effects on mothers' choice of employment. While the data sample is small compared to previous literature on child care prices and employment, the chapter provides a rare analysis of effects from child care quality on female labor supply.

The final chapter summarizes and discusses the main results and considers their policy implications. Several future research avenues based on the chapters are also suggested.

Chapter 2

Child Care and Female Labor Supply: A Meta-Analysis

2.1 Introduction

Child care subsidies are an important element of developed welfare states. It is an attractive policy option, given that it can serve both reallocation goals favoring young parents, and efficiency goals through increased female labor force participation. To test the benefits of child care subsidies, since the late 1980s, a sizable body of literature appeared investigating the impact of child care prices on female labor force participation. This chapter reviews the elasticity estimates of this literature, discussing its findings and attempting to explain why elasticity estimates differ so significantly across studies.

A puzzle arises when considering the empirical findings over time and across countries. While earlier studies, such as Blau and Robins (1988), find a large elasticity of labor force participation with regards to child care prices in the United States, there is a large variation in results when more recent studies from the US and also Europe are taken into account. These findings inevitably challenge the hypotheses relating high female labor participation with child care subsidies. As an example: Bettendorf et al. (2012) finds that an increase in the subsidy rate of child care has a very small impact on aggregate labor supply in the Netherlands. A striking example of variation over time can be seen in Sweden. The elasticity value calculated by Gustafsson and Stafford (1992) is close to 0.9 while Lundin et al. (2008) find no significant effects from child care prices on labor force participation with tight confidence bounds.

A number of explanations can and have been offered for the variation in estimated elasticity sizes. A first set of explanations refers to study-specific factors such as methodology employed or sample characteristics; a second set takes into account macro level factors such as the overall female participation rate or the flexibility of the labor market. Aggregate indicators and institutional factors are inevitably ignored in micro level studies since they are essentially exogenous to the analysis and show no variation. However, a meta-analysis of the results found in the literature can scrutinize both groups of explanations for variation in elasticity estimates, since we can compare results from different labor markets and samples. The estimates we collected allows for a study of estimates from 12 countries and spanning 30 years.

The rest of the chapter is organized as follows. Section 2 provides a brief overview of the basic labor supply models with child care and discusses how macro level factors may be interpreted within the micro level model. Section 3 discusses the literature findings and describes the methodologies used, the differences in sample characteristics and the macro level trends in elasticity estimates over time and across countries. Section 4 presents a meta-regression, testing the various explanations offered in sections 2 and 3 for the variation in elasticity sizes. Section 5 concludes.

2.2 Theoretical Framework

2.2.1 Basic Models of Child Care and Labor Supply

The importance of child care prices for female labor supply was recognized in Heckman (1974) which is called the 'pioneering study in the field' by Blau and Robins (1988). The most commonly found theoretical basis for analyzing the effect of child care prices on labor supply in the literature is grounded on the simple static labor supply model with modifications to include child care prices and choices. A number of variants of the static model have been proposed with varying degrees of flexibility by including child care quality, unpaid care and household decision making (Blau and Robins, 1988; Connelly, 1992; Ribar, 1995; Powell, 1997; Tekin, 2007). The general setup and implications of the models do not differ significantly. This section begins with the simplest version of the static labor supply model and adds two of the more common and empirically relevant modifications: unpaid care and quality.

The starting point of labor supply models involving child care is a utility function consisting of consumption C and leisure l. The maximization problem has two constraints; time $l+h=1$ and budget $C=y+(w-p)h$ where y is non-labor income, h is hours of work and p is price of formal child care. In this basic budget constraint, the price of child care is treated like a tax on wages with each hour of work requiring the purchase of an hour of child care. The implications of changes in the price of child care are thus similar to a change in taxation, with higher prices making it less likely for the effective wage rate $w-p$ to exceed the reservation wage.

Two common modifications to the basic model found in the theoretical side of the literature are unpaid care and quality. The addition of unpaid care to the model relaxes the assumption that hours of formal child care use must be equal to working hours and provides an explanation for the observation of working women who do not use formal care. Instead, as in Blau and Currie (2006), the sum of unpaid care hours u and formal child care hours h^f may be assumed to be equal to working hours, $u+h^f=h$. If the costs of unpaid care are assumed to be equal to the caregiver's market wage, the shadow price of unpaid care could be added directly into the budget constraint. A simpler approach is to add the leisure l_c of the unpaid caregiver directly into the utility function. Subject to the time constraint of the informal caregiver $u+l_c=1$, there is a disutility associated with the use of unpaid care. If child care quality is equal across care types, the price of child care can be related to unpaid care with the condition $\frac{U_{l_c}}{U_u}=p$. This equality implies that the cost of an extra hour of formal care is equal to that of informal care. The price of formal care can then be used as an indicator of the shadow price of informal care.

A second modification is based on relaxing the assumption that the quality of child care is homogenous among maternal care and other care types, by defining and including in the utility function a term for quality given by $q=(1-h,C)$. It is assumed that care quality is improved by maternal care and consumption goods. Following Ribar (1995), the resulting maximization problem from these two modifications is given by:

$$\underset{h,h_f}{max} U(C,1-h,1-l,q) \tag{2.1}$$

Subject to the consumption constraint $C=y+hw-h^f p$ and time constraints $h+l=1$, $l_c+u=1$ and $h^f+u=h$. Manipulating the first order condition of this problem with respect to h, the reservation wage can be defined as:

$$w_r = p + \frac{U_l + U_q Q_l}{U_c + U_q Q_c} \tag{2.2}$$

The equation (2.2) is similar to the result that Ribar (1995) derives with slight differences in the way unpaid care and child care prices are defined. Evaluated at the corner of the budget constraint where $h = 0$, the comparative statistics are self-evident. Child care prices, marginal utility of leisure for the mother and the informal caregiver as well as higher quality maternal care raise the reservation wage and lower the likelihood of employment. High marginal utility from consumption and a large marginal contribution to child quality from consumption goods which can be purchased by labor income lower the reservation wage.

2.2.2 Macro Level Factors

In estimations of the female labor force participation elasticity with respect to child care prices, the micro nature of the data means that the institutional factors are exogenously given. [1] In this section, some potential macro level factors which may influence the variation in elasticity estimates.

One explanation for the differences in the sizes of the elasticity over time is pointed out by Lundin et al. (2008) in their study of child care and labor supply in Sweden. The authors argue both that further reductions in child care prices have diminishing effects, and that high labor supply countries are unlikely to experience a significant rise in participation by lowering prices. On the aggregate level higher labor force participation decreases the elasticity size simply because the denominator in the elasticity calculation becomes larger. High participation figures can also signal factors influencing the individual participation decision. Countries with high female labor force participation may already have cheap and readily available formal child care or can make use of alternative informal care arrangements, both of which will diminish the effects of further reductions in child care prices. Furthermore, if other structural factors, such as the wage structure or working hour flexibility, contribute to high female employment, the effect of the child care prices on participation may be limited. Going back to equation (2.2), if the effective wage is well above the reservation wage for most mothers, small changes in child care prices may not have any detrimental effects for participation.

[1] This generalization applies with the exception of a minority of recent natural experiments that exploit differences in child care subsidies and child care reforms (Cascio, 2009; Lundin et al., 2008).

Somewhat paradoxically, low participation figures can also signal characteristics associated with smaller elasticity sizes. Cultural or structural impediments have been shown to constrain the impact of child care (Van Gameren and Ooms, 2009). Using European data, Lippe and Siegers (1994) find that women in very traditional networks are unlikely to respond to changes in wages. As child care subsidies provide a similar incentive, their effects can be influenced by social norms and the definition of gender roles. Cross country comparisons support this point. Results from a low female employment economy, Italy, and a transitional economy, Russia, are on the lower end of elasticity estimates in the literature (Del Boca et al., 2004; Lokshin, 2004). Combining these two arguments, one from within the labor supply framework and the other from cultural factors, elasticity sizes are expected to be smaller in labor markets with very low and very high female participation. Going back to equation (2.2), this may be because parents in such countries view maternal care as much higher quality than non-maternal child care.

Another plausible source of variation in elasticity estimates is the prevalence of part-time work. Working part-time lowers the demand for formal, full-time child care, while at the same time allowing women to provide informal child care. These two effects of part-time work are expected to increase both the demand and supply of informal child care which can be substituted for formal child care. The substitution of informal care for formal care has been offered up as an explanation as to why previous literature reviews find that the price elasticity of demand for formal child care is much larger than the labor supply elasticity with regards to the price of child care (Blau and Currie, 2006). The economic theory supports the intuition behind this explanation. If potential caregivers have more leisure due to part-time work, given that the benefit of providing an hour of care needs to equal to the cost of losing an hour of leisure, the shadow price of informal care is expected to be low. Since the price of formal care equals to this shadow price at the margin, a higher proportion of informal care is to be expected in settings with high part time incidence. European estimates are supportive of this line of reasoning. Using a natural experiment from Norway, Havnes and Mogstad (2011a) have found that increasing formal child care coverage resulted in a crowding out of informal care rather than having any discernable effects on women's employment. In the "part-time economy" of the Netherlands, estimates are uniformly smaller or insignificant compared to the rest of the literature (Wetzels, 2005; Bettendorf et al., 2012). Although parents opt for more formal child care in the Netherlands when prices are decreased, this simply crowds out informal care without having much effect on participation decisions. In turn, the lessened reliance on formal child care diminishes the effects increasing child care prices have on employment decisions. As a result, countries with high part-time rates would be expected to have lower labor supply elasticity estimates.

Yet another macro level factor which may influence the variation in elasticity is the income inequality. While no functional form to the utility maximization problem was assigned in equation (2.1), the common assumption of concavity and hence diminishing marginal returns to consumption and leisure may have implications for the elasticity size. If utility from consumption is diminishing, the effects of changes in prices will be higher for low income parents. Kimmel (1995) remarks on the prevailing notion that high child care costs are a much bigger obstacle to employment for low income mothers. The rate of poverty or income inequality may thus partly explain the striking difference between estimates from European countries with more extensive safety nets and the more minimal welfare state in the USA. European estimates of participation elasticity are mostly around 0.1 while American estimates tend to be much larger. The variation in the degree of income inequality and its implications for child care choices may be another explanation for the difference in elasticity sizes.

2.3 A Review of the Empirical Literature

In order to analyze the impact of the different explanations for the variation in estimated elasticity sizes, we surveyed the literature in three steps. First, the Google Scholar search engine was used, searching for the key phrases "labor supply child care elasticity" and "labor force participation child care elasticity." Second, the references of several articles were scanned. Third, the literature review of Blau and Currie (2006) and the literature review of Wrohlich (2006) were used, the former for studies on the US and Canada, and the latter for studies from Europe. In total around 50 articles are considered and 45 estimates are included in the table 2.1 for analysis from around 40 different articles. The majority of the studies consider labor supply as labor force participation rather than weekly or annual hours worked. Several studies report, we include only the participation elasticity in these cases. The studies estimating hours elasticity such as Heckman (1974) and Averett et al. (1997) had to be eliminated since the comparison of the two is not possible in terms of the elasticity sizes. Estimates used in this chapter are listed in table 2.1. The sample is made up of 10 working papers, indicated with bold writing in table 2.1, and 28 articles from peer-reviewed journals.

Table 2.1 shows the calculated elasticity, sample size, year of the data used, country and the data source for each article. Although higher child care prices make participation less likely, the elasticities are reported as positive values to make comparison easier. There are a few cases such as Blau and Robins (1991), Del Boca et al. (2004), Wetzels (2005) and Van Gameren and Ooms (2009) where there is no elasticity estimate reported because the coefficient on price is close to 0 and insignificant. In these cases, we set the elasticity to 0.

While using the estimated elasticity rather than a regression coefficient as the effect size makes a comparison between studies convenient, a number of studies calculate the elasticity based on regression coefficients. Hence, there is often no direct standard error available to use as a precision factor. In many of these cases, the t-statistic of the regression coefficient used to calculate the price elasticity could be transformed to impute the standard error. However, in some cases, even this is not possible because utility derived from each activity such as work and leisure is calculated based on a regression analysis and a simulation model is used afterwards to check for the elasticity. Since many studies are missing clearly defined standard errors for elasticity estimates, we used the sample size of the study as the main precision factor. Larger samples are simply assumed to give more precise estimates of employment elasticity. Only study that does not report its sample size is Kimmel (1995), since that study focuses on the low income single parents we take the half value of the single parents from the same dataset that is used in Kimmel (1998) as an approximation.

Table 2.1 shows the variation in elasticity estimates across the literature. The participation elasticity ranges from nearly 1 in Kimmel (1998) and Connelly and Kimmel (2003a) to close to 0 in Lundin et al. (2008) and Wrohlich (2006). Below, we discuss the possible causes for the variation.

2.3.1 Role of Sample Characteristics and Methodological Choices

The subsamples that the researchers limit their research to such as the marital status, income level or child ages are not consistent across the studies in table 2.1. These characteristics are likely to have an impact on the elasticity size. The findings with

Table 2.1: Literature Summary

Authors / Publishing Year	***Elasticity***	***Sample Size***	***Year***	***Country***	***Data Source***
Doiron and Kalb (2005) - Single	0.02	5305	1997	Australia	CCS SIHC
Doiron and Kalb (2005) - Married	0.75	1116	1997	Australia	CCS SIHC
Gong et al. (2010)	0.287	4048	2006	Australia	HILDA
Powell (2002)	0.2268	9886	1988	Canada	CNCCS
Baker et al. (2005)[a]	0.236	33788	1998	Canada	NLSCY
Cleveland et al. (1996)	0.388	3976	1988	Canada	CNCCS
Beblo et al. (2005)	0.05	3444	2002	Germany	SOEP
Wrohlich (2004) [b]	0.025	1345	2002	Germany	SOEP
Wrohlich (2006)	0.02	3213	2002	Germany	SOEP
Del Boca et al. (2004)	0	3213	1998	Italy	Bank of Italy
Van Gameren and Ooms (2009)	0	737	2004	Netherlands	SCP
Wetzels (2005)	0	865	1995	Netherlands	AVO
Kornstad and Thoresen (2007)	0.12	2400	1998	Norway	IDS
Lokshin and Fong (2006)	0.46	1505	1999	Romania	RCCES
Lokshin (2004)	0.12	2169	1995	Russia	RLMS
Gustafsson and Stafford (1992)	0.872	166	1984	Sweden	HUS data
Lundin et al. (2008)	0	683471	2002	Sweden	Statistics SE
Jenkins and Symons (2001)	0.09	1235	1989	UK	LPS
Viitanen (2005)	0.138	5068	2000	UK	FRS
Anderson and Levine (1999) - Full sample	0.511	12458	1992	USA	SIPP
Anderson and Levine (1999) - Married	0.463	9045	1992	USA	SIPP
Baum (2002) - Full sample	0.185	2801	1991	USA	NLSY
Baum (2002) - Low income	0.584	691	1991	USA	NLSY
Blau and Hagy (1998)	0.2	2426	1990	USA	NCCS
Blau and Robins (1988)	0.38	6170	1980	USA	EOPP
Blau and Robins (1991)	-0.028	10670	1984	USA	NLSY

[a] This paper was published as Baker et al. (2008), but the final version does not seem to include the elasticity calculation. The coefficients for employment seem to be the same in both versions.

[b] The labor supply model is estimated for a much larger sample but not all households have young children. The price selection equation is based on 1345 observations for children under 6.

Literature Summary cont.

Authors / Publishing Year	***Elasticity***	***Sample Size***	***Year***	***Country***	***Data Source***
Cascio (2009) - Single	0.505	68827	1950-1990	USA	Census
Cascio (2009) - Married	0.505	225028	1950-1990	USA	Census
Connelly (1992)	0.2	2781	1984	USA	SIPP
Connelly and Kimmel (2003b)	0.37	1523	1992/3	USA	SIPP
Connelly and Kimmel (2003a) - Married	0.446	4241	1992/3	USA	SIPP
Connelly and Kimmel (2003a) (2003b) - Single	0.984	4241	1992/3	USA	SIPP
Han and Waldfogel (2001) - Married	0.35	30931	1992	USA	SIPP
Han and Waldfogel (2001) - Single	0.6	10187	1992	USA	SIPP
Herbst (2010)	0	74042	1999	USA	CPS / SIPP
Hotz and Kilburn (1991)	-0.01	2032	1986	USA	NLSY
Kimmel (1995)	0.346	348.5	1988	USA	SIPP
Kimmel (1998) - Single	0.219	697	1987	USA	SIPP
Kimmel (1998) - Married	0.923	2350	1987	USA	SIPP
Ribar (1992)	0.74	3738	1984	USA	SIPP
Ribar (1995)	0.088	3769	1984	USA	SIPP
Rusev (2006)	0.012	3060	1997	USA	SIPP
Tekin (2007)	0.121	4029	1997	USA	NSAF
Michalopoulos and Robins (2000) c	0.259	1762	1989	USA/Canada	CNCCS
Michalopoulos and Robins (2002) c	0.156	13026	1989	USA/Canada	CNCCS

regard to martial status are somewhat ambiguous. Among the studies that estimate elasticity values for both groups Doiron and Kalb (2005) and Han and Waldfogel (2001) find single women to be more responsive while Kimmel (1995, 1998) finds the reverse to hold true. Michalopoulos and Robins (2000, 2002) have investigated both groups over two articles and have also found a smaller elasticity for married women. For samples with lower income, the estimated elasticity by Kimmel (1995) for single women is larger than her later study for a general sample (Kimmel, 1998). Baum (2002) also finds a relatively large elasticity above 0.5 for a sample with low income. The only exception is Tekin (2007), who finds a relatively low elasticity for a low income sample, but this is more likely due to the methodology used in that study, which seems to produce generally smaller estimates.

Methodological choices can in fact play a large role in explaining the differences between the estimates. A large portion of the studies included in this analysis use a structural model to predict wages and child care prices, which are in turn used to estimate the employment elasticity using a limited dependent variable model such as probit (see for example Connelly (1992); Ribar (1992); Kimmel (1998); Anderson and Levine (1999)). Beyond endogeneity issues in directly estimating the labor supply equation, wages and often formal care prices may not be available for non-working mothers. Heckman (1979) sample selection specification is universally used for the wage equation to avoid selection biases in OLS regressions. The identification of prices is more varied as the price variable and the available identifying variables depend on the survey used. Kimmel (1998) is rare in showing explicitly that the definition of price (and model specification) can be an important factor by performing several robustness checks. Although her original estimations use price per hours worked, the estimated elasticity becomes much closer to the value found in Ribar (1992) when the price variable is shifted to price per hour of child care utilized.

Besides the econometric specifications with two outcomes, employment or non-employment, several researchers such as Michalopoulos and Robins (2000, 2002), Lokshin (2004) and Tekin (2007) use multinomial choice models. The basic setup involves defining the combinations of full-time or part-time work and unpaid or paid care as multiple discrete outcomes. The number of these outcomes depends on the categorical detail that the study reaches into, with Tekin using 7 and Michalopoulos and Robins using 12 categories. The econometric caveat in these models is the possible correlation between the error terms in the estimation of the different indirect utility equations. The standard multinomial logit model imposes the assumption of independence of the irrelevant alternatives, meaning that the error terms should be uncorrelated. However, this assumption may be too strict to hold for female labor supply and child care. Women with strong tastes for leisure may be less likely to work and have lower wages. Similarly, women who work full-time may prefer formal care over informal care. Blau and Hagy (1998) and later Lokshin (2004) and Tekin (2007) allow for correlations in the error terms by using discrete error structures similar to those found in duration models as introduced by Heckman and Singer (1984). The estimated elasticities of 0.1 to 0.2 from the literature using multinomial logit models are uniformly in the lower end of the estimates, a remark also made by Tekin (2007).

Apart from structural modeling, the second broad identification methodology in the literature is natural experiments. These studies exploit changes in child care policies to identify the effects. Although they do not identify as many parameters as structural models, reduced form natural experiments may be more useful in identifying the effects of price changes in European countries where publicly funded child care that has little variation in price. Lundin et al. (2008), Baker et al. (2005) and Cascio (2009) are the studies that fit into this category. A few studies also use subsidies explicitly within a structural model to estimate price effects, but the overall modeling strategy in these cases do not differ from other structural studies based on child care expenditure data (Rusev, 2006; Tekin, 2007; Herbst, 2010).

2.3.2 Country and Time Trends in Elasticity Estimates

With regard to the macro level factors, the elasticity estimates in the literature show some visible patterns. Figure 2.1 shows the decline in elasticity sizes over the years that the samples in the studies are from. The question is whether this decline is due to a change in women's responsiveness to child care prices. Limiting the comparison to the United States, Tekin (2007) and Herbst and Tekin (2010), who use relatively more recent samples from 1997 and 1999 respectively, find much smaller elasticities then estimates based on samples from the 80s or early 90s. Similarly the only European estimate of participation elasticity from a sample from 1980s, the study of Gustafsson and Stafford (1992) in Sweden, finds the largest elasticity value in Europe among the studies presented in table 2.1. However, it is difficult to directly conclude that the smaller elasticity findings are merely due to changes in population's responsiveness to child care prices, given the fact that there has been a noticeable shift in econometric techniques to multinomial choice models that find smaller elasticities

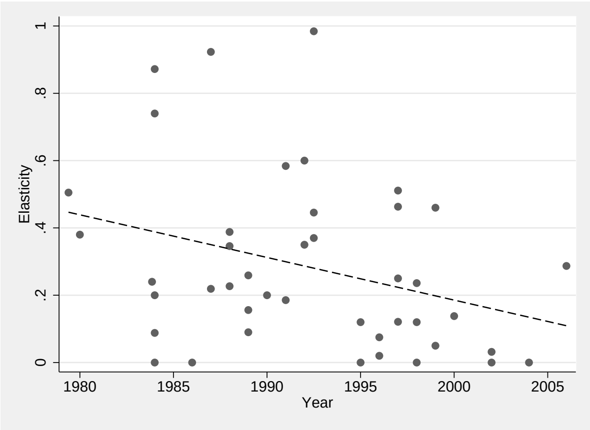


Figure 2.1: Elasticity Estimates over Time

in the last decade. Furthermore, the estimates from Europe that have become more common over time, tend to be smaller than estimates from the US.

The difference between estimates from Europe and the US is quite large. Taking the mean of the two subsamples shows a mean of 0.18 for the European and Canadian studies and 0.36 for the US studies. The large discrepancy between the participation elasticity found in the two continents seems to point towards a role for macro level factors discussed in section 2.2 in determining responsiveness to child care prices. Higher child care costs in the USA may be an explanation as well, as it would directly affect the elasticity calculation by increasing the nominator. However, the costs of child care vary between countries depending on marital status and income levels and the costs are not universally higher in the US according to analysis based on OECD data from early 2000s (Immervoll and Barber, 2006).

In short, for a proper interpretation of different or conflicting results in the literature, readers need to take into account what choices the researcher made with regards to methodology and sample characteristics and the context of the study. In the next section, we provide a more rigorous test for these causes of differences in elasticity estimates using meta-regressions.

2.4 Meta-Regression

In this section, we use multivariate regressions to investigate the impact various methodological or macro level factors may have on the elasticity estimates. Meta-regressions are quite varied in the literature, ranging from simple OLS models to random effects models where the effects are weighed by the inverse of variances (Nelson and Kennedy, 2009). In their review of meta-analyses in environmental economics literature, Nelson and Kennedy (2009) suggest that some sort of weighing and heteroskedasticity robust standard errors are crucial for meta-regressions. Simulations of Stanley and Doucouliagos (2013) suggest that weighted least squares (WLS) (with inverse of the standard error as weights) are preferable to more widely used random effects estimators. Since we do not have standard error information for all estimates, we use the sample size as a precision factor, a strategy that was previously followed in the literature (Oosterbeek et al., 2004). Our WLS models similarly use the sample sizes of the studies as the weights. The regression equation estimated is given as:

$$\beta = X\gamma + Z\phi + \varepsilon_i + v_i \tag{2.3}$$

In equation (2.3), β is the elasticity estimate of each study, X are controls for sample and methodological characteristics, and Z represents the macro level factors. ε is the error term. To control for sample differences, indicator variables are added for studies that estimate effects for only low income, married or single women and a control is added for child age. Child age is defined either by the summary statistics showing average age when available or by the median value of the child age range used. Different specifications, such as using dummy variables for different age ranges, did not lead to different significances. For the methodological differences, controls for natural experiments and multinomial or discrete models are added. Once we control for natural experiments and discrete choice models, the base category is mostly made up of probit estimates. Additional variables for identifications based on changes in subsidy rates or the number of control variables used in labor supply regressions had no significant effects. This finding is not necessarily due to an actual lack of effect from the number of control variables. Constructing a harmonized variable for the number of control variables that allows for comparison between studies is difficult. Econometric methodology often determines the difference in the number of control variables used. It is not surprising to find that natural experiments have fewer control variables. The difficulty of harmonizing characteristics across studies may limit the explanatory power of the meta-regressions. It is also worth noting that three German studies, Beblo et al. (2005), Wrohlich (2004) and Wrohlich (2006) all use the same data source and similar methodologies. In this case, we simply took the average of the three estimates, which are quite similar in size, and summed up their sample sizes to weigh the resulting average estimate.

Figures for female labor force participation and the incidence of part-time workers among employed women have been retrieved from OECD (2010) statistics. The labor force participation values are for women between the ages 15 and 64. There are a few years missing in the data for incidence of part-time work in various countries, for these the closest possible year is used instead. Interpolating for part-time is avoided since it correlates and varies with business cycles (Buddelmeyer et al., 2004). Lokshin (2004) is a rather extreme case for part-time work, with an incidence of 4.7%, and is controlled for separately in the regressions through a dummy variable for the study. Not including this dummy leads to smaller effects from part-time work. The degree of income inequality is measured by Gini coefficients. Data are retrieved from an updated version of the dataset compiled by Deininger and Squire (1996), along with more recent figures from the World Bank Indicators and CIA's the World Factbook (2011). Once again several years of data were missing, and data from the closest year available was used instead in these cases. In case of studies with several years of data, we took the average of the years or used the median year. Most child care studies use one or two years of data and the variation in aggregate variables tends to be limited. One exception is (Cascio, 2009), who uses 5 separate waves of data from 1950, 1960, 1970, 1980, 1990. In that case, we weighted year, labor force participation and Gini coefficients variables for each year with the sample sizes of the treatment groups used for married and single women's employment estimation [2]. We could not take the weighted mean for part-time work since there is no data for the earlier years. Instead, we used the value of the year closest to the median year of 1970, which was 1979. There does not seem to be much variation in part-time work over the years, and the models that include the part-time variable give similar results when the Cascio (2009) study is excluded.

[2] We acquired labor force participation rate for the United States in 1950 from St. Louis FED since OECD data starts in 1960. FRED (Federal Reserve Economic Data) seems to use a slightly different definition and reports lower values in later years compared to OECD statistics. The difference is most likely because FRED data reports rates for all women instead of women between 15 and 64. Dropping the 1950 value from the weighted mean has little effect on the results.

Table 2.2: Determinants of Elasticity Sizes

Model	**1**	**2**	**3**	**4**	**5**
Married		0.086	0.098	0.075	0.095
		(0.140)	(0.154)	(0.149)	(0.152)
Single		0.136	0.13	0.137	0.134
		(0.178)	(0.177)	(0.183)	(0.176)
Low income		0.215	0.168	0.232	0.179
		(0.133)	(0.156)	(0.145)	(0.180)
Child age		-0.034	-0.033	-0.027	-0.016
		(0.024)	(0.019)	(0.026)	(0.022)
Natural experiment		0.066	-0.054	0.058	-0.098
		(0.102)	(0.065)	(0.103)	(0.071)
Multinomial		-0.016	-0.096	-0.058	-0.158
		(0.098)	(0.092)	(0.103)	(0.096)
FLFP (%)	0.200**	0.262***	0.132	0.241***	0.079
	(0.081)	(0.071)	(0.084)	(0.067)	(0.086)
FLFP2 (%)	-0.001**	-0.002***	-0.001	-0.002***	-0.0005
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Part-time (%)	0.00006	-0.008**	0.002		-0.007
	(0.005)	(0.004)	(0.005)		(0.005)
Gini coefficient				0.0004	-0.030**
				(0.010)	(0.013)
Sample year	-0.018**		-0.021***		-0.021***
	(0.007)		(0.007)		(0.008)
F-statistic FLFP	3.27**	27.90***	2.69*	15.15***	3.83**
Observations	43	43	43	43	43
R-squared	0.732	0.704	0.778	0.69	0.797

Results for five separate weighted least square regressions based on 43 elasticity estimates are presented in table 2.2. OLS estimates with robust standard errors are presented in Appendix 2A. The labor force participation variables appear to be at least jointly significant in all models. Its impact however may be overestimated in models without a control for the sample year. Since participation rates are higher in later studies, adding a control for the sample year decreases the size of the coefficients and their significance. The relationship between the elasticity size and female participation rate appear to be positive but inverse U-shaped. In OLS models, the inverse U-shape is less apparent and the coefficient on the square term is extremely small. When checking the exact effects at different rates, the positive impact of female participation on elasticity peaks at about 69% in model 1, around 71% in model 3, and around 83% in model 5 where the square term has a smaller coefficient. Many developed countries are now near or have surpassed these values. To put the results into context, according to OECD statistics, the female labor force participation rate among OECD countries was at 61.5% in 2009, while the corresponding value was 65.8% for EU-15 countries.

It is possible to argue for reverse causality based on the coefficients of female labor force participation because elasticity values may imply that governments can take advantage of participation responsiveness by increasing child care subsidies. However, the female participation figure used here is for the entire working age population of women rather than only women in an age group with high fertility who are most likely to be affected by changes in child care prices. Furthermore, while reverse causality argument could be plausible for the positive effect found, it is not for the diminishing effects. If any quadratic effects were expected at all, the prediction would be to have a convex relationship, such as that of a usual cost function, between participation rates and elasticity sizes if the elasticity size was driving participation rates higher.

Of the two other macro level issues that were discussed in section 2, part time work appears to be correlated with smaller elasticity estimates. Part-time work appears to be much more significant and consistent in OLS estimates shown in the Appendix. The difference may be due to smaller sample sizes and thus lower weights for estimates from countries with high part-time rates. Studies from the Netherlands could be introducing a spurious correlation here if the low elasticity values found in Dutch studies are due to some other underlying factor. However, adding a control for estimates for the Netherlands does not change the significant effects found although it does make the coefficient smaller and less significant.

Gini coefficient has a significant effect in model 5 but not in model 4. The results seem to be rather inconclusive for the Gini coefficient to be counted as a major explanatory factor for the different elasticity sizes found in Europe and the USA. Even in model 5, the significant effect is economically rather small since the Gini coefficient ranges only between 25.8 and 40.8. The higher participation rates in countries like Sweden and Norway and differences in the incidence of part-time employment may be stronger explanations for the differences in findings.

The methodological and sample characteristics included in the regressions have lower precision in WLS estimates because many of them are based on a very small number of observations. The low income sample control has a positive coefficient, which is consistent with literature predictions. Child age has a negative coefficient, which would fit with the hypothesis that child care prices matter more for mothers of young children and infants. In the OLS models, using a multinomial choice model appears to lead to smaller estimates. Natural experiments also tend to be correlated with smaller elasticity estimates in OLS models and two WLS models. The large standard errors for the natural experiment variable in particular may be due to the low number of studies that use natural experiments.

To test the sensitivity of the results, several unreported robustness checks were performed. We fitted the WLS models without the three natural experiment estimates, which have very large sample sizes and might be skewing the results. The effects seem fairly similar overall but the labor force participation and part-time effects become slightly more significant. The effect size for labor force participation peaks at around 65% in model 5 in that case. Second, we fitted OLS models with the log of the sample size as a control variable. The sample size variable has a negative significant effect but the other variables have similar effects except for the Gini coefficient in model 5, which turns insignificant. As a final test, we checked the consistency of the standard errors by clustering them at the study level. Since most studies in our sample have 1 or at most 2 estimates from them, this does not seem to affect the results since we already use robust standard errors. On the other hand, not using robust standard errors leads to largely insignificant relationships in the OLS models.

2.5 Discussion

The effect of child care prices on female labor supply is largely agreed and found to be negative despite some recent studies showing smaller or insignificant effect sizes in various countries. This has led to a widespread view of child care subsidies as a rather strong policy tool for increasing female participation. However, comparison across studies is made difficult due to differences in methodological choices and macro level factors. While the European (and Canadian) literature shows a mean employment elasticity with regards to child care prices of about -0.18, the American only subsample's mean is -0.36. The underlying reasons for these differences could help to give a better understanding of what is being reported from micro-level research.

While tentative, the review of the empirical literature and the meta-regression of section 4 show that a some of the variation in elasticity sizes can be explained through methodological differences and macro level factors. While statistically insignificant in the the models, married samples tend to have smaller elasticity estimates while low income is associated with larger elasticity sizes. Model choice, especially discrete choice models of varying sophistication, can similarly alter the size of the participation elasticity. Beyond study specific issues, labor market contexts determine the importance of child care prices. The female participation rate has a positive yet diminishing relationship with the elasticity size, while part-time work decreases it. For high participation or high part-time countries like Sweden, Norway or the Netherlands, further policy focus on child care prices might be less effective from an employment perspective. Similarly, directly borrowing high participation countries' family policies may not dramatically increase employment in countries with very low participation rates. Considering alternatives to costs, such as quality of care offered, could help induce untapped participation effects. Already, quality of care has been examined in terms of child care demand and supply (Blau and Hagy, 1998), but its links to labor supply needs further analysis.

The hypothesis that effects may be smaller in some settings does not invalidate the use of child care subsidies for other policy goals. More broadly, child care subsidies serve as targeted income transfers towards parents and promote horizontal equity by improving the position of parents who choose to work. Evidence from Germany, for which studies generally find low participation elasticities, shows that child care subsidies can help improve fertility (Haan and Wrohlich, 2011). Furthermore, Havnes and Mogstad (2011b) find that subsidized child care has a positive effect on child development in Norway. However, this finding is not universal. The effect of child care subsidies is actually negative in the United States according to Herbst and Tekin (2010). For the United States, the authors make a case for encouraging both high quality care and employment. Focusing only on providing cheap child care through subsidies to improve participation of low income mothers may have an adverse effect on child development (Baker et al., 2008; Herbst, 2013).

The review of the empirical literature on child care prices and labor supply highlights two areas for further research. Hours elasticity estimates are underrepresented even though the intensive margin is becoming more important due to higher female participation rates in most developed countries. Secondly, other aspects of child care such as quality and availability are areas that more research is needed in, especially given that quality or flexibility in child care services may involve trade-offs with the price of care. In chapter 6, we study how child care quality might be linked with female labor supply within a structural model.

2.6 Appendix 2A

Table 2.3: OLS Estimates with Robust Standard Errors

Model	**1**	**2**	**3**	**4**	**5**
Married		0.02	0.042	-0.009	0.035
		(0.108)	(0.098)	(0.119)	(0.098)
Single		-0.03	0.007	-0.038	0.027
		(0.137)	(0.120)	(0.143)	(0.120)
Low income		0.075	0.065	0.124	0.065
		(0.134)	(0.145)	(0.140)	(0.160)
Child age		0.011	0.001	0.018	0.007
		(0.020)	(0.019)	(0.025)	(0.019)
Natural experiment		-0.133	-0.146	-0.093	-0.148
		(0.149)	(0.117)	(0.149)	(0.098)
Multinomial		-0.173**	-0.154*	-0.173*	-0.189**
		(0.078)	(0.079)	(0.094)	(0.083)
FLFP (%)	0.017	0.053	0.025	0.038	0.052
	(0.085)	(0.114)	(0.087)	(0.105)	(0.083)
FLFP2 (%)	-2E-05	-0.0003	-8E-05	-0.0002	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Part-time (%)	-0.006*	-0.010***	-0.007*		-0.013***
	(0.003)	(0.002)	(0.004)		(0.004)
Gini coefficient				0.004	-0.023**
				(0.013)	(0.011)
Sample year	-0.013*		-0.012		-0.009
	(0.007)		(0.008)		(0.007)
F-statistic FLFP	8.89***	3.39**	12.56***	3.17*	11.07***
Observations	43	43	43	43	43
R-squared	0.266	0.291	0.352	0.169	0.389

Chapter 3

Labor Market Effects of Parental Leave in Europe [1]

3.1 Introduction

Within Europe, leave schemes for parents have been going through a steady evolution. Maternity leave has existed for most of the 20th century, reinforced by the 1952 ILO convention on maternity protection. In 1992, the EU adopted directive 92/85/EEC on paid maternity leave, making 14 weeks of paid maternity leave the minimum in the EU member states, though many countries already had more generous schemes. In 1996, directive 96/34/EC of the European Council obliged member states to introduce unpaid parental leave that enables parents to care full-time for their child over a period of three months. More recently parental leave legislation was again on the EU scene, as the Council directive 2010/18/EU increased the length of (unpaid) parental leave to four months, extended its application to atypical employment contracts and made at least one month of parental leave exclusive to each parent. Further legislations are being debated in the European Parliament with regards to increasing paid maternity leave from 14 weeks to 20 weeks and introducing paid paternity leave for a minimum of two weeks.

The changes in maternity and parental leave legislation appear to be in line with the emphasis on increasing the female participation rate as articulated in the Lisbon

[1]This chapter is a slightly different version of the article published in the Cambridge Journal of Economics. The article version can be cited as: Akgunduz, Y.E. and Plantenga, J. Labour Market Effects of Parental Leave in Europe, 37(4), 845-862.

agenda. At the same time, there seems to be little knowledge on the aggregate labor market effects of parental leave legislation. An earlier study by Ruhm (1998), covering eight EU countries and Norway and using data from the period between 1969 and 1993, found positive effects of paid leave on female labor force participation at the cost of declining wages. Since Ruhm's widely cited study, there has been little aggregate level research on the impact of parental leave legislation on labor market outcomes. An update seems reasonable given that the data used are aging, only a small number of countries are covered and the longer unpaid parental leave is not taken into account. This study therefore examines the effects of leave legislation on employment rates, average weekly hours worked, wages, and vertical occupational segregation, covering 16 countries for the period between 1970 and 2008.

Legislative information is acquired from "Comparative Maternity, Parental Leave and Child Care Database" of Gauthier and Bortnik (2001) and is supplemented by findings from other sources on maternity and parental leave legislation. The aggregate level indicators for the aforementioned labor market outcomes are collected from the databases of OECD, Eurostat and ILO. The results of our analysis indicate increases in participation rates that diminish with length and generosity of leave schemes. While pure participation numbers may not increase dramatically, there is strong evidence of increases in weekly working hours. Concurrently, according to the effects on proxy indicators, a decrease is observed in high skill wages alongside an increase in vertical occupational segregation.

The structure of the article is as follows. The second section discusses justifications for maternity and parental leave, a theoretical background on the effects of leave legislation on labour market outcomes and the findings of some recent empirical studies. The third section introduces the available data and connects them with the fourth section that presents the difference-in-difference methodology used. The fifth section contains the results of our empirical analysis. Finally, the sixth section concludes.

3.2 Theoretical Considerations and Literature Review

In leave research, nearly every type of leave has multiple names, making it necessary to clarify the terms used throughout this study. Two different types of leave are usually categorized: on the one hand maternity and paternity leave and on the other parental leave (De Henau et al., 2007). Maternity and paternity leaves are typically concentrated around the birth of a child and cover a relatively short period of time with high replacement rates; most maternity leave entitlements cover a period between 14 and 20 weeks. Paternity leave is even shorter, often measured by days. In contrast, parental leave tends to be longer, ranging from an extra 12 weeks to three years, and has lower replacement rates. When not making a distinction, these two types will be simply called leave.

Leave legislation has effects on three distinct areas of welfare, and most of the research and debate on its effects are concentrated around these. Historically, maternity leave legislation was passed for paternalistic reasons, namely to protect the health and well-being of mothers and new-born babies. As the earliest international legislation on the issue, the 1919 ILO convention on maternity leave states that women are not permitted to work for six weeks after childbirth. The proposed health effects for infants continue to constitute the first section of the research on the impact of leave legislation. As the findings on child health appear to be positive (Ruhm, 2000), this positive externality is used as a justification for mandating leave. The second area on which leave policy may have an impact on is that of fertility rates, although this issue is not fully resolved by scholarship on the topic. The general findings tend to be positive, though the combination of short parental leave durations and high fertility rates in some countries give some ambiguity to the results (Gauthier, 2007; Lalive and Zweimüller, 2009). Fertility concerns continue to be a prime driver for leave legislation. The most recent example was in Germany where low fertility of working women led to a switch to an earnings related benefit system for the first year of parental leave. The final area that leave legislation has an impact on is the labor market and, specifically, the labor market outcomes of leave-takers (which in most instances are women). At least some maternity leave is the norm around childbirth and the discussion in Europe focuses more on the optimal length of leave rather than questioning whether or not to have leave legislation at all. This chapter studies in specific the effects of leave legislation on female labor market participation (both in rates and in hours worked), the relative wage level and the share of women in high level occupations. More specifically, we focus on European countries, all of which had some sort of maternity or parental leave in 1970.

Ruhm's (1998) study explains the labor market effects of mandated leave within a supply and demand framework. The effects are realized both before and after motherhood. Before pregnancy, the opportunity for future leave increases the supply of

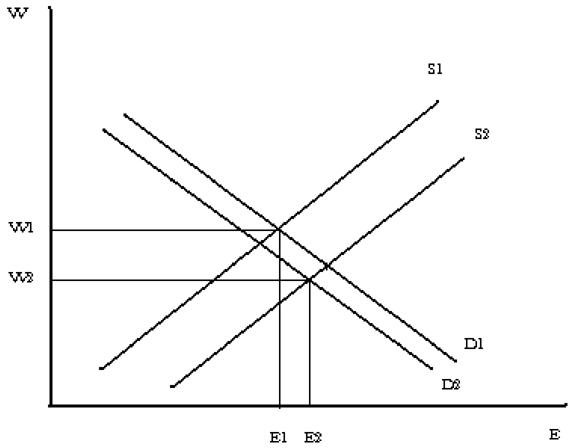


Figure 3.1: Labor Market Consequences of Parental Leave

prospective parents.[2] After leave has been taken up, it provides a continuing labor market attachment. Combined, these effects lead to a shift of the supply curve to the right. At the same time, the training and replacement costs for firms cause a contraction in demand. The magnitude of the change in demand relative to the increase in supply determines the effects of parental leave. A possible outcome is illustrated in figure 3.1; the introduction of leave legislation, due to the specific shifts in the demand and supply curves, leads to an increase in employment and a decrease in wages. A more positive outlook on parental leave could argue that the demand curve also shifts to the right as firm-specific human capital is protected and workers become more productive. A sufficient shift may even lead to an increase in wages alongside employment.

Ruhm's framework, at least in the post-birth analysis of leave effects, is implicit in other research (see below) predicting positive employment effects from leave legislation. Starting point is that in the absence of job guarantees parents will drop out of the labor market for a longer period of time. In this case, parental leave facilitates

[2]A simple way to show the supply increase would be to consider a wage-utility function containing both pecuniary wages and leave opportunities: $W = U = U(w,L)$ with the usual assumptions $U_w > 0, U_L > 0$. For the sake of simplicity, if the returns are linear and homogenous under specific levels of leave and pecuniary wages: $U = w + L$, if $\frac{U_w^*}{U_L^*} = 1$. A government increasing leave from 0 to L* will have increased total gain from work even if wages were to drop. The potential for the increase is greater where wages are higher. A similar model is used by Han-Werner (2003) in explaining the improvement of working conditions.

swifter and higher rates of return to work because the job security provided eliminates future search costs and the loss of firm-specific human capital. Additionally, the job security provided by parental leave may have a positive effect on participation and wage gaps between men and women. Protecting firm-specific human capital during early years of motherhood could lead to better opportunities for women to continue their careers. This would be consistent with the demand curve in figure 3.1 shifting to the right as a result of increased human capital and productivity.

Contrary to the above framework, there are findings pointing towards a negative participation and productivity effect of parental leave take-up (Ondrich et al., 1996, 2002). Mandated leave can lengthen time out of work and create artificial interruptions. This would have an adverse effect on supply, because parents take leave instead of continuing to work, and on demand, because time out of work deteriorates leave-takers' human capital and productivity. Hence, both wages and employment are likely to drop. It is worth stressing that while the drop in wages is uniformly predicted by both, the starting points are different. In the latter, wages do not drop because of additional supply, but rather due to longer periods out of work and decreased productivity of leave-takers.

Empirically, there exist a number of studies utilizing individual level data to determine the effects of leave legislation on wages, employment and occupational segregation. Using data from Germany, Ondrich et al. (2002) find a substantial decrease of 18% in wages for every year spent on parental leave. Buligescu et al. (2009) conclude that the negative effects of parental leave take-up on wages are fairly minimal or non-existent in the long run while being substantial in the short run. The rebound in wages after an initial decrease upon return from parental leave seems faster than other types of career interruptions. Gupta et al. (2008) review family policies in the Nordic countries and conclude that there may be negative effects from the presence of long-term parental leave legislation on wages and consequently for career opportunities of women. Supporting the job security approach, Waldfogel (1998) observes that leave coverage diminishes the wage penalty on return for returning women. Long-term absence from work of any kind has negative effects on wages, but it is not clear whether parental leave decreases or amplifies these effects during early motherhood.

The findings with regards to the impact on employment are rather positive. Among aggregate level studies, Jaumotte (2003) has similar findings to those of Ruhm (1998). Female employment rates seem to increase in response to leave legislation, but the positive effects diminish as leave duration is increases. Pronzato (2009) also finds positive (yet diminishing) effects from leave as the provided job security increases the proportion of mothers returning to work. Making leave paid, however, decreases participation in the first year after birth. Leave periods lasting more than a year may have an adverse effect on the return rates, both in terms of lengthening time out of work and decreasing the probability of returning to work in the long run (Ondrich et al., 1996). Despite the generally positive results on participation, there are findings that increased participation rates through generous welfare schemes come at the cost of increased vertical segregation. For example, Mandel and Semyonov (2005) argue that policy induced higher labor force participation translates into a more gender segregated labor market, with detrimental effects for the income inequality between men and women. Clearly, these potential negative side effects of welfare policies do not imply that lower participation would be preferable for gender equality. Rather the results suggest that increasing the female participation rate does not necessarily imply a higher score in all dimensions of gender equality.

3.3 Data

Data used in this study is a combination of several sources for EU-15 countries and Norway. Legislative information on leave is a combination of the Comparative Maternity, Parental and Childcare Database (Gauthier and Bortnik, 2001), OECD's family database, ILO's legislation archives and a number of articles and previous studies (Plantenga and Remery, 2005; Nyberg, 2004). Different sources are likely to provide different data, usually as a result of different definitions of maternity and parental leave. In such cases, the definitions laid out in the previous section were used to infer what constitutes different types of leave in a given country. Additional checks on maternity leave were done using the Social Security Programmes Throughout the World series. The values for some years were missing between 1999 and 2008, but the years with changes in leave could be found from Eurofound's European Industrial Relations Observatory (2010). In cases where no reforms were found in Eurofound's observatory or other sources, it is assumed that no changes took place. As such, the effects that we estimate will be based on the reforms that we could find.

The basic characteristics of any leave legislation can be summarized through its length, the level of benefits during leave, flexibility options such as part-time leave and eligibility criteria. While it would be ideal to combine and measure the effects of all these characteristics, the focus inevitably shifts to benefits and length. Maternity leave varies little across Europe, with high replacement rates and durations of 14 to 20 weeks. The benefit difference between parental leave and maternity leave can and does vary considerably. One example is provided by the Danish reforms in 2002 which give mothers the right to 18 weeks of maternity leave with a wage replacement rate of 100% and 32 weeks of parental leave with benefits equaling 80% of last earned wages. On the other end of the spectrum, Austrian legislation includes 16 weeks of maternity leave with 100% replacement of last earned wages and 104 weeks of parental leave with low flat rate benefit for the first 78 weeks and no benefits for the last 26 weeks. Benefit levels are important, more so for parental leave, because they are the main determinant of the take-up rates, which in turn determines the actual impact of leave. The most straightforward method in taking into account these factors would be weighting duration with benefits. Unfortunately, data is difficult to find for benefits in earlier years and longer unpaid leave would be completely ignored. Instead, benefit thresholds are used for weighting parental leave.

Following Plantenga and Remery (2005), leave is weighted by 33% if the replacement level is between 0% and 33%, by 66% if the replacement rate is between 33% and 66% and 100% if the replacement rate is above 66%. In case of flat rate benefits, we calculated the relative scores, by combining different sources. In case of Belgium and Germany, Gauthier and Bortnik 's dataset puts the flat rate benefits below 33% of the average previously earned wages for most years. For Austria and Luxembourg, the benefit amount of 2006 and 2007 is calculated as a percentage of the real median wage of the total working population as reported by OECD statistics and net household income given by Eurostat. In earlier years until 1999, Gauthier and Bortnik 's dataset shows no benefits for Austrian parental leave. The 2006 benefit amount is around €450 in Austria and €1840 in Luxembourg. As both values are close to 33% and 66% thresholds respectively, Austrian parental leave is weighed by 33% and Luxembourg's by 100%. Austria undergoes several smaller reforms after 1990 [3], which changes the benefit rate depending on the number of children, but the benefits remain around 33% of real median wage and net household income. Luxembourg's flat rate is slightly below 66% of median earnings in 2007, but more than 66% of median net income according to Eurostat and is thus treated as 100% in weighting. Appendix 3A shows the results of weighing for 2008. For ma-

[3] Austrian parental leave was extended to two years in the second half of 1990. Since the reform occurs in the second half, we coded the change in 1991. The results do not change much if the reform is coded in 1990.

ternity leave, data on benefit levels in nearly all years is available and is used directly for weighting. As a result the weighted (maternity and parental) leave is calculated as: (Maternity Leave Duration*Maternity Leave Benefits%)+(Parental Leave Duration*Weight%).This weighted leave variable combining both maternal and parental leave is used as the main independent variable in the analysis section.

There are a few country specific peculiarities in parental leave legislation that should be mentioned. In Sweden and Finland, maternity leave and parental leave legislations are combined in the dataset since their legislation makes little distinction between them. French legislation provides parental leave benefits for a second or later child. These benefits are ignored and French parental leave is considered unpaid in the present dataset. Some countries, including Spain and Italy, provide family based parental leave rather than individual entitlements to leave. As the take-up of men is usually small (5% in Italy and Spain and merely 1% in France (Fagan and Walthery, 2007), we presume that in such cases all leave is taken by the mother. Finally, it has to be taken into account that the focus on national legislation leaves out employer inputs in designing leave facilities. Collective agreements play a large role in determining the benefits levels in several countries (Plantenga and Remery, 2005). As an extreme example, Dutch legislation for parental leave is unpaid while civil servants are entitled to a 75% of last earnings benefit during their leave. In this case, if women are more concentrated in public sectors which are more likely to use supplementary collective agreements for leave, the effects captured by the changes in official legislation in this study may not be identical to the effects of leave facilities in general.

Figure 3.2 shows the average durations over time of the three leave variables for EU-15 and Norway. The first is the duration of maternity leave, the second of the weighted (maternity and parental) leave and the last line of the longer parental leave.

While most leave legislation started with a short maternity leave right of about 3 months, introduction of parental leave policies has complicated the legislative landscape. Some clusters with regard to parental leave legislation are nevertheless visible. Countries like Finland, Sweden and Denmark assume a dual earner family and support their leave legislation with generous allowances. The male breadwinner model was more active in Germany (at least until 2007), Austria, Portugal and Spain. These countries have long durations of leave with low allowances, where one partner can take care of the newborn and the other stays in the labor force. United Kingdom,

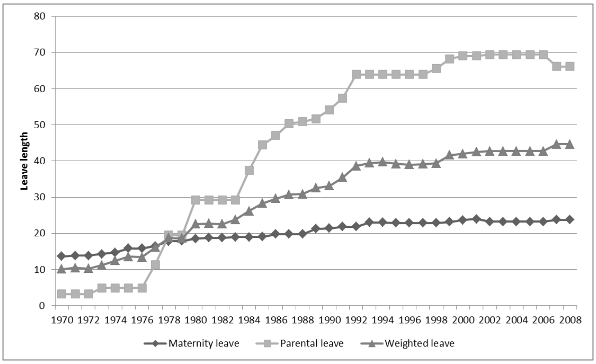


Figure 3.2: Development of Leave in EU-15 and Norway

Ireland and Greece have more market oriented legislations and the state mandated leave duration is short. Netherlands diverges from this minimalist approach through greater use and rights for part-time work that allows a combination of leave and care, fitting the needs of the prevalent one and a half earner family.

Gendered employment to population rates were drawn from OECD's (2010) statistics database. Statistics are available for the entire period between 1970 and 2008 except for missing data in several countries between the years 1970 and 1982. A major problem in studying the impact of parental leave through aggregate participation data is that OECD counts parents on parental leave as employed. This may lead to some overestimations of the labor market effects. OECD database also provides the usual weekly hours worked data for women between the ages 25 and 54. Finally, absolute numbers of working age populations from the OECD database are used in weighting.

Gendered wage data are from ILO statistics (2010) and cover a period between 1970 and 2008. This relatively complete dataset is available only for the manufacturing sector. Data were drawn from both 'Key Indicators of the Labour Market' (KILM), a research tool prepared by ILO, and the underlying database LABORSTA, which has data from years that are not yet in KILM. Definitions sometimes differ between countries as wages are collected from slightly different samples such as "employees" or "wage earners". We tried to select the most complete data avaialable for each country. In general, the data from KILM are used and some additions were made from LABORSTA. In most countries, there is a switch in the time series from hourly wages to monthly wages, but this does not seem to cause any large shifts in the outcome variables since we take the difference in logs between the genders' wages. Dropping extreme changes in gender wage gaps (more than 0.05 in the difference between the logs) does not seem to affect the results. Unfortunately, no gendered wage data could be found for Spain and Italy. There are also a large number of missing years for each country's dataset. While the manufacturing wage data is the most complete for the period under study, it comes with strong limitations. The high level of horizontal occupational segregation indicators observed across Europe stems mostly from the concentration of women in public sector or service jobs (Bettio et al., 2009). Thus manufacturing wages give a wage indicator for only a small portion of employed women.

For a small number of countries, namely United Kingdom, Portugal, Finland, Netherlands, Luxembourg and Denmark, there are wage data from different sectors in the period between 1994 and 2008. Out of these sectors, "financial intermediation" has the highest wages in all countries and data drawn from LABORSTA for this sector is used as a proxy for high skill wages. Once again there are some, though fewer, missing years of data. Hourly wages are available for most countries while a few only report monthly wages. All wage data used in regression analyses have been deflated by the consumer price index and multiplied by the purchasing power parities found in the OECD database to make the values comparable across years and countries. The base year used by OECD in calculating the consumer price index is 2005.

The final labor market outcome studied, vertical occupational segregation, is based on an indicator constructed from data provided by Eurostat. Through labor force surveys, the number of professionals, managers, legislators and senior officials are made available. The number of women between the ages 15 and 39 in these jobs as a share of total number of persons working in these jobs within the same age group is used as an indicator for vertical occupational segregation. Data exists for the period between 1992 and 2009. There are only a few missing cases in earlier years.

The evolution of the averages of three of the labor market outcomes studied in this study can be found in figure 3.3, which shows the gender gaps in wages and employment, and vertical segregation. Wage data used is nominal manufacturing wage data. The results for wages should be interpreted with care because missing cases in various years for different countries can cause a false impression of large changes in the average wage gap. The employment gap shown is between men and women aged 25 to 34. Interestingly, the decline in the employment gap is not fully reflected in a decline in the wage gap, which seems to have stabilized around 20%.

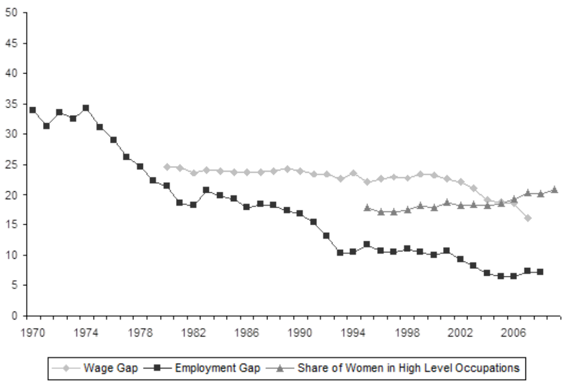


Figure 3.3: Evolution of Labor Market Outcomes in EU-15 and Norway

Wage gap calculated as the difference between genders as a proportion of male wages: $W_f - W_m / W_m$
Employment gap calculated as the difference between genders as a proportion of male employment to population ratio: $\frac{(E_f / P_m - E_m / P_m)}{E_m / P_m}$

Various demand side and institutional explanations, such as the role of workplace characteristics and the wage structure, have been offered for the puzzling persistence in the pay gap despite decreasing gaps in experience and education (Blau and Kahn, 2000; Rubery et al., 2005). Lastly, the trend for the shares of employed women working as managers, legislators, senior officials and professionals as an indicator of vertical occupational segregation is mapped out. While there are no dramatic changes, there is a steadily rising trend.

3.4 Methodology

The model setup used is nearly identical to Ruhm's (1998) original DDD model. This section simply provides a summary and describes any changes with regard to the data and model used. The starting difference-in-difference model exploits changes in leave over time. Subscript j denotes country and t time while f and m refer to female and male respectively.

$$Y_{fjt} = a_1 S_f + \beta_1 C_j + \beta_2 T_t + \delta_f L_{jt} + \gamma_1 S_f C_j + \gamma_2 S_f T_t + \varepsilon_{fjt} \tag{3.1}$$

$$Y_{mjt} = a_1 S_f + \beta_1 C_j + \beta_2 T_t + \delta_m L_{jt} + \gamma_1 S_m C_j + \gamma_2 S_m T_t + \varepsilon_{mjt} \tag{3.2}$$

Where, Y_{fjt} is the log natural form of a labour market outcome for women, C_j is a country effect and T_t is a time effect. The effects of leave, L_{jt}, are assumed to be exclusive to the treatment group of women. Finally, S_f is the gender specific intercept. To remove endogenous country and time effects, a DDD model is estimated by subtracting equation (3.1) from (3.2), which results in:

$$\Delta Y_{jt} = a_1(S_f - S_m) + \gamma_1(S_f - S_m)C_j + \gamma_2(S_f - S_m)T_t + (\delta_f - 0)L_{jt} + (\varepsilon_{fjt} + \varepsilon_{mjt}) \tag{3.3}$$

Simplifying and adding country-specific time trends to avoid biases resulting from gender specific time effects, the final estimation is reached. Ruhm (1998) notes that keeping the age groups constant across men and women would account for cohort effects. Additionally, in all the regressions in section 5, a quadratic term is added along with lags for both leave and leave squared. The quadratic term is added to allow for diminishing or increasing effects depending on the length of leave, rather than limiting the results to linear effects over all lengths of leave.

$$\Delta Y_{jt} = a + \beta_1 C_j + \beta_2 T_t + \delta_1 L_{jt} + L_{jt}^2 + L_{jt-1} + L_{jt-1}^2 + \beta_3 C_j T_t \tag{3.4}$$

For a correct interpretation of the outcomes, a few caveats of the methodology need to be taken into account. So far the notation used is for men as the control group and women as the treatment group. This may not be completely accurate as father's use of available parental leave days has reached nearly 20% in Sweden, up from around 2% in 1978 (Nyberg, 2004). If the take-up of leave has the same effects for men as for women the assumption of $(\delta_f - 0)L_{jt}$ will not hold and there may be an underestimation if the effect of leave is identical for men and women. Furthermore, households can make decisions jointly, and a decision to work or take leave can have an impact on the labour supply of the partner. Instead of an identical impact on men and women, men could lower their labour supply using parental leave if the participation effect is positive for women. The overall bias, if any, can then be positive or negative. To correct for this bias, older men in the age range between 45 and 54, who may be less likely to use parental leave, are used as the control group. There is no data on when men generally become fathers, and this is simply a guess at the age group where men's leave eligibility for parental leave may be low. Due to differing availability of data between indicators, the age difference between women and men was only incorporated into the analysis of participation rates. For women, total fertility rates are known for different age groups. Despite heterogeneity, the fertility rates seem to peak either in the 25 to 29 or 30 to 34 age range across European countries. While helping to target the investigation to those who are most likely to be affected by leave legislation, using the rather narrow age range of 25 to 34 leaves out women who delay childbearing past age 34. Since education and motherhood age have been shown to be positively correlated (Hank, 2002), the sample may be skewed towards the less educated. If such women are more responsive to the supply side incentive leave legislation offers or benefit more from job security, this can cause an overestimation of short-term participation effects.

The final point that needs to be mentioned is on weighing. Heteroskedasticity is certain given the difference in population sizes. The results are reported using both ordinary least squares (OLS) with robust standard errors and weighted least squares (WLS) as an additional check. The second uses the weighting procedure as described and employed by Ruhm (1998) that was introduced by Blackburn (1997).

3.5 Results

3.5.1 Participation and Leave

Two different dimensions of economic participation will be taken into account. The first is labor market participation, captured by the employment to population ratios. The second dimension is intensity, referring to weekly hours worked. The results in table 3.1 show the effects of weighted leave on the employment to population ratio of women between the ages 25 and 34 and 15 and 64. For the age group 25-34, the control group used is men between the ages 45 and 54 though results using a control group of men between the ages 25 and 34 are also presented. For the age group 15-64, the control group is men aged between 15 and 64; whatever effect parental leave may have on recent fathers, it should be fairly minimal on the full working age sample. Leave variables are lagged twice and lagged variables account for a large portion of the effects as shown in Appendix 3B. This is most likely because changes in leave legislation might happen mid-year and it takes some time until the labor market fully absorbs their effects.

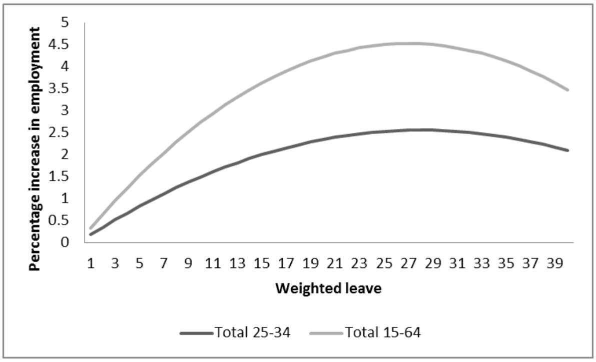


Figure 3.4: Participation and Leave

For each combination of treatment and control groups, two models are fitted using robust and WLS specifications indicated in the second row. The final row shows the p-values for a joint F-test on all leave related variables including both lagged and current variables for leave and leave squared. The difference between the robust and WLS specifications is small. In all models, the p-values show significant positive effects from the leave variables with significant negative effects from the quadratic terms, at least at the 10% level. The positive effects, combined with negative coefficients on quadratic terms, means that participation increases with leave, but the effects diminish with the length of leave. Note that the standard errors presented in parentheses underneath the sums of coefficients are for current leave and leave squared. There is some evidence of a lagged effect as the significance of effects is mostly due to two year lagged leave variables. Models fitted using men between ages 25 and 34 as the control group instead of men aged between 45 and 54 results in positive, but smaller effects. The significance does not change. The smaller effects may be due to underestimation if male labor market behavior in this age group is affected similarly to that of women by leave legislation.

Based on the regression coefficients, it is possible to calculate the estimated effects of different lengths of weighted leave. This gives a rough idea about the optimal levels of leave. Figure 3.4 plots the effects. The coefficients from the robust standard error estimations are used. The results indicate that the main participation effect of leave is for the age group with higher fertility rates. The impact on the total employment to population ratio declines proportionally if the entire female labor force is taken into account. The optimal amount of weighted leave, combining both maternity and parental leave, to maximize employment is 28 weeks for the age group between 25 and 34. The effect at this point is more than 2.5%. The optimal length is slightly smaller, about 6 months, for the 15 to 64 age group and results in an increase in participation of more than 1.8%. Earlier macro level studies of Ruhm (1998) and Jaumotte (2003) had found about 20 weeks of leave to be optimal. The optimal duration found here may be longer due to the inclusion of unpaid leave rather than only paid leave. As in previous macro level studies, it is unclear how large of an overestimation [4] there is due to counting employees on leave as employed while collecting data for employment to population ratios. According to 1992 data from Denmark, 1.25% of female employment was on maternity leave, including other family reasons this number becomes 2.6% (OECD, 1995).

Table 3.1: Employment/Population Ratios of Women and Weighted Leave

Age	25-34 (n=490)		15-64 (n=505)		25-34 (n=505)	
(Control Group)	(Men 45-54)		(Men 15-64)		(Men 25-34)	
Specification	Robust	WLS	Robust	WLS	Robust	WLS
Leave	0.18	0.19	0.15	0.17	0.08	0.07
	(0.14)	(0.13)	(0.09)	(0.10)	(0.12)	(0.11)
Leave2	-0.32	-0.33	-0.30	-0.31	-0.22	-0.21
	(0.15)	(0.17)	(0.11)	(0.13)	(0.14)	(0.14)
p-value	0.096*	0.071*	0.072*	0.016**	0.027**	0.004***

*** p<0.01, ** p<0.05, * p<0.1. *Leave* is divided by 100 for ease of interpretation. p-values are from F-tests performed on all leave variables including lagged leave instead of only *Leave* and $Leave^2$. Change in participation due to a given length of leave is calculated using the formula: $\Delta = exp(\delta_1 Leave_t + \delta_2 Leave_{t-1} + \delta_3 Leave_{t-2} + \delta_4 Leave_t^2 + \delta_5 Leave_{t-1}^2 + \delta_6 Leave_{t-2}^2$

Parental leave may also have an effect on hours worked, if without a period of leave women would prefer shorter working hours to balance their work and family lives. Intensity of work could be measured through several indicators including the rate of part-time work, annual hours worked and weekly usual hours worked. In this chapter, weekly usual hours worked is preferred. Part-time work does not differentiate between numbers of hours of work while annual hours worked may be influenced by differences in sectors' vacation lengths. The treatment group is women between the ages 25 and 54. The control group is men between 25 and 54. Table 3.2 presents the results, using the same format as table 3.1. The sums of the lagged and current

[4] A very rough estimate can be made by considering total female employment and leave duration. Assuming 1.5 children on average, 6 months of leave take-up and an average of 30 years of working life between retirement and market entrance for an employment to population ratio of 50%, leave take up will account for 1.25% of the EP ratio.

leave variables show positive effects. The negative effects for the quadratic leave variable indicate diminishing returns. Under both specifications, the effects are significant at the 1% level. A right to 30 weeks of paid leave increases working hours of women by about 6%. The positive results reinforce the notion that without paid parental leave as a time out of work, women may be pushed into combining work and care through shorter working hours. This can have long lasting effects, considering evidence of strong attachments to contract types whether it is a part-time or full-time contract (Blank, 1989). Parental leave thus provides a policy tool to promote more full-time labor market attachment.

Table 3.2: Working Hours of Women and Weighted Leave

Age	25-54 (n=359)	
(Control Group)	(Men 25-54)	
Specification	Robust	WLS
Leave	0.27	0.28
	(0.05)	(0.06)
Leave2	-0.22	-0.23
	(0.05)	(0.07)
p-value	0.0***	0.0***
30 Weeks Leave	6.05%	6.42%

*** p<0.01, ** p<0.05, * p<0.1. Leave variables are divided by 100 for ease of interpretation. p-values are from F-tests performed on all leave variables including lagged leave instead of only *Leave* and $Leave^2$. Change in participation due to a given length of leave is calculated using the formula: $\Delta = exp(\delta_1 Leave_t + \delta_2 Leave_{t-1} + \delta_3 Leave_{t-2} + \delta_4 Leave_t^2 + \delta_5 Leave_{t-1}^2 + \delta_6 Leave_{t-2}^2$

3.5.2 Wages, Occupations and Leave

Previous studies hint that the positive effects of leave on participation may be overshadowed by its impact on wages and career opportunities. The aggregate effects are studied through three dependent variables; wages in manufacturing, wages in financial intermediation and share of women working as professionals, legislators, senior officials or managers. The former is an indicator for low skill wages, the second for high skill wages and the final for occupational segregation. All three dependent variables are once again in the log-natural form. No differentiation between age groups can be made for the wage data, but the occupational data is for the group aged between 15 and 39. The results of OLS and WLS estimations for all three dependent outcomes are presented in table 3.3.

Table 3.3: Wages and Occupations of Women and Weighted Leave

	Manufacturing Wages		Financial Wages		High Level Occupations	
	(n=327)		(n=133)		(n=268)	
Control group	(Men)		(Men)		(Men)	
Specification	Robust	WLS	Robust	WLS	Robust	WLS
Leave	0.04	0.04	-0.01	-0.09	-0.24	-0.26
	(0.07)	(0.09)	(0.28)	(0.37)	(0.42)	(0.49)
Leave2	-0.03	-0.04	-0.43	-0.34	0.70	0.68
	(0.08)	(0.10)	(0.37)	(0.50)	(0.37)	(0.51)
p-value	0.50	0.78	0.00***	0.07*	0.039**	0.20

*** p<0.01, ** p<0.05, * p<0.1. Leave variables are divided by 100 for ease of interpretation. p-values are from F-tests performed on all leave variables including lagged leave instead of only *Leave* and $Leave^2$. Change in participation due to a given length of leave is calculated using the formula: $\Delta = exp(\delta_1 Leave_t + \delta_2 Leave_{t-1} + \delta_3 Leave_{t-2} + \delta_4 Leave_t^2 + \delta_5 Leave_{t-1}^2 + \delta_6 Leave_{t-2}^2$

Table 3.3 shows results for weighted leave related variables from six different models, once again using the two specifications for each of the measures that are used and indicated on the top row. In all cases the control group is composed of males in the corresponding age group. The p-values on the bottom row indicate significance at least at the 10% level for effects on high skill wages and occupational segregation, with the exception of the WLS specification for occupational segregation. The effects on occupational segregation also become less significant if we use data up to 2008 but the results remain similar and turn highly significant if we drop the second lag. No significant effects could be found for manufacturing wages. In general, the effects on wages and occupations are more concentrated on current leave rather than lagged leave. Compared to supply side factors, demand controlled factors seem to respond faster to legislative change. Figure 3.5 shows the predicted effects of different durations of leave using coefficients from the robust standard error estimates. According to our calculations, the effects of leave on the share of women in high level occupations are small, about -1% at 30 weeks, but significant.

The difference between the effects on the two wage categories, manufacturing wages and financial intermediation wages, is striking. While the effects on manufacturing wages are insignificant, financial intermediation wages decreases noticably as leave length increases, dropping around 6% at 30 weeks. The insignificance of the effects on manufacturing wages seems surprising given that Ruhm (1998) had found a negative effect from generous parental leave on manufacturing wages. His interpretation is that the increase in supply, the decrease in human capital for longer rights to leave, and replacements costs would drive wages down. Despite downward pressure on wages due to an increase in supply, the insignificant effects on manufacturing

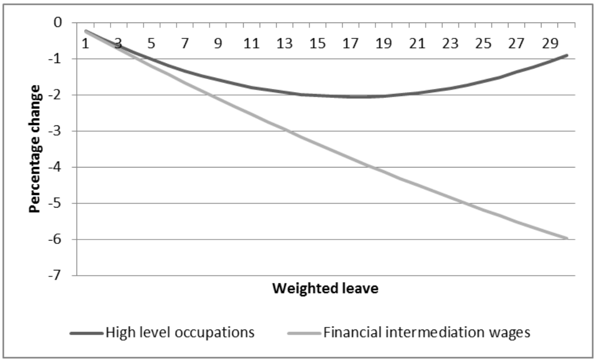


Figure 3.5: Wages, Occupations and Leave

wages can perhaps be explained by their proximity to the minimum or starting wages which would constrain how low wages can fall. An increasing in supply can not explain the effects on financial intermediation wages, while the positive participation effects were small and diminishing, the negative effects on financial intermediation wages are large and exponential.

The second explanation refers to the impact of human capital. If manufacturing jobs are essentially unskilled, any potential negative effects of long-term interruptions due to parental leave on human capital would be insignificant. Employees in skilled sectors may be more prone to perceived loss of human capital from leave take-up. While parental leave legislation protects firm-specific human capital to a certain degree by providing job protection, general human capital will depreciate during leave. The different impact of parental leave on general and firm specific human capital is important if firm-specific human capital and general human capital influence wages in different sectors and skill levels to varying degrees. Using German data, Dustmann and Meghir (2005) conclude that low skilled workers benefit highly from firm-specific tenure, but less so from experience while high skilled workers' wages increase with both tenure and experience. This would suggest that firm attachment and job security provided by leave legislation is more relevant for manufacturing wages than for financial intermediation wages. Or, stated differently, high skilled wages would be more likely to decrease substantially due to depreciation of general human capital during parental leave.

Cost of training and hiring of replacements for leave takers is the last explanation offered for a decrease in wages due to leave legislation. Considering the increased use of temporary contracts and availability of temporary agency workers across Europe, employers may be less likely to have large replacement costs which would be passed on to potential parental leave takers. Nevertheless, replacement costs can still be substantial in high skill sectors, especially if availability is low and firm provided training is costly. According to Eurostat data from 2009, while more than 15% of employees with a highest education level of secondary schooling have temporary contracts in the EU, this proportion is less than 10% for employees with tertiary education. The difference in availability and firms' preference for hiring temporary workers in manufacturing and financial intermediation sectors might therefore explain part of the differences seen in effects from parental leave on these two sectors.

3.6 Conclusions and Discussion

Based on the history of maternity and parental leave in Europe, leave legislation in the future is unlikely to see any declines, but will go through further optimization. The general impression that female employment to population ratios are improved through more generous leave certainly helps the case for it, especially if one considers the Lisbon targets that focus heavily on participation rates. The results in section 5 support the idea that job-protected leave can increase female labor supply (though the effects may be overestimated due to data collection methods). The positive participation effect, however, comes at a cost. 30 weeks of parental leave is roughly estimated to slightly decrease the share of women in high level occupations and women's wages in financial intermediation by 6%. As such, negative demand side effects seem to dominate for high skill workers. Compared to Ruhm's (1998) previous estimations, results here suggest a slightly lower increase in employment accompanied by a larger decrease in high skill wages while the negative effect on manufacturing wages becomes insignificant. One redeeming factor is the higher number of hours worked by women when leave legislation becomes more generous.

The analysis this chapter has presented is undoubtedly rough, given the aggregate and cross-country nature of the data and the inevitability of a large number of missing values and reforms missed. The cross-country perspective has meant that portions of leave schemes are effectively ignored because the focus is purely on national level legislation. Since take-up rates remain unknown for most of the years in many countries, strong assumptions had to be made to allow for cross-country comparisons and to use men as the control group. Data used is only a proxy for high and low skill wages, indicators for which long running gendered datasets are generally difficult to find. Despite these limitations, the aggregate approach helps place parental leave within the more macroeconomic framework of employment, working hours and wages. The study thus provides a general indication of the effects it has had and may have over the years in Europe.

The results suggest, leave policy can be approached in two ways. The first is to exploit the noticeable participation effects from short periods of leave and aim for paid leave for women of about 20 weeks, including both maternity and parental leave. This would both minimize the negative effects on high skill wages while providing the bulk of the participation benefits. The second would be to purely concentrate on participation. In that case, a paid leave period of about 30 weeks seems to give the best results, which is longer than previous estimates of 20. The longer leave period suggests that unpaid leave, which was not taken into account by Ruhm (1998), may have a stronger effect than expected. Since positive effects were also found for weekly hours worked, the 30 week option would be particularly preferable in countries where part-time work has a lasting and negative impact on future earnings and career opportunities.

Applying the results to the EU level, the case for extending minimum parental or maternity leave is not strong from a purely labor market perspective. The current legislation of 14 weeks of paid maternity leave and 12 weeks of supplementary parental leave seems to capture most of the positive effects for participation rates. Anything beyond the current minimum is likely to have minimal impact on participation while potentially decreasing wages and causing occupational segregation. However, this may not apply to paternity leave which was outside the scope of this article and may have different effects on the labor market positions of men and women. Furthermore, it would be imprudent to design leave legislation for mothers based only on labor market effects given the large impact parental leave can have on fertility and child health. Instead, the results of this paper should be used in lieu with findings from research on fertility and health effects of leave to consider the full costs and benefits of maternity and parental leave.

3.7 Appendix 3A

Table 3.4: Parental and Maternity Leave Duration/Benefits in 2008

	Maternity / Paid Leave		Parental Leave		Weighted Leave
	Duration	**Replacement Rate**	**Duration**	**Weight**	
Austria	16	100	104	33	50.32
Belgium	15	77	12	33	15.51
Denmark	18	100	32	100	50
Finland a	43.5	90 and 66	112.5	33	67.97
France	16	100	156	33	67.48
Germany b	14	100	104	66 and 33	83.16
Greece	17	100	13	33	21.29
Ireland	26	80	14	33	25.42
Italy	21.5	80	43	33	31.39
Luxembourg	16	100	26	100	42
Netherlands	16	100	13	33	20.29
Norway	42	100	52	33	59.16
Portugal	17	100	104	33	51.32
Spain	16	100	156	33	67.48
Sweden	60	80			48
UK	26	35.7	13	33	13.57

a) In Germany, the recent 2007 reform changed the right to parental leave to one year and the replacement rate to 67%. Parents can opt for spreading the benefit over two years. To take into account both options, first year is weighted by 66% and the second by 33%.
b) In Finland, a recent reform in 2007 increased replacement rates to 90% in the first 56 days of leave.

3.8 Appendix 3B

Table 3.5: Parental leave and employment

Age:	25-34		15-64		25-34	
Control group:	Male 45-54		Male 15-64		Male 25-34	
	Robust	WLS	Robust	WLS	Robust	WLS
$Leave_t$	-0.0865	-0.0841	-0.0312	-0.0164	-0.0998	-0.1067
	(0.1389)	(0.1334)	(0.0906)	(0.1013)	(0.1211)	(0.1089)
$Leave_t^2$	0.0169	0.0144	-0.004	-0.0195	0.0053	0.0122
	(0.1531)	(0.1696)	(0.1116)	(0.1296)	(0.1397)	(0.1380)
$Leave_{t-1}$	0.0151	0.0168	0.0347	0.0353	0.0018	0
	(0.1779)	(0.1681)	(0.1116)	(0.1285)	(0.1610)	(0.1373)
$Leave_{t-1}^2$	-0.0197	-0.0204	-0.0644	-0.0626	0.014	0.0143
	(0.1927)	(0.2156)	(0.1345)	(0.1655)	(0.1794)	(0.1755)
$Leave_{t-2}$	0.2533*	0.2530*	0.1499	0.1535	0.179	0.1792
	(0.1491)	(0.1361)	(0.0987)	(0.1028)	(0.1402)	(0.1111)
$Leave_{t-2}^2$	-0.3209*	-0.3210*	-0.2293*	-0.2304*	-0.2377	-0.2372*
	(0.1693)	(0.1747)	(0.1190)	(0.1328)	(0.1575)	(0.1423)
F-test (p-value)	0.096*	0.071*	0.072*	0.016**	0.027**	0.004***
Observations	490	490	505	505	490	490
R-squared	0.971	0.971	0.986	0.985	0.981	0.981

Table 3.6: Parental leave and average working hours

Age:	25-54	
Control group	Male 25-54	
	Robust	WLS
$Leave_t$	0.0651	0.0692
	(0.0475)	(0.0596)
$Leave_t^2$	-0.0343	-0.0364
	(0.0541)	(0.0658)
$Leave_{t-1}$	-0.0065	-0.002
	(0.0503)	(0.0748)
$Leave_{t-1}^2$	0.021	0.0173
	(0.0563)	(0.0815)
$Leave_{t-2}$	0.2083***	0.2164***
	(0.0611)	(0.0670)
$Leave_{t-2}^2$	-0.2047***	-0.2128***
	(0.0747)	(0.0760)
Observations	359	359
R-squared	0.988	0.989

Table 3.7: Parental leave, wages and occupational segregation

Outcome:	Manufacturing wages		Financial wages		Occupational segregation	
Control group:	Male 45-54		Male 15-64		Male 25-34	
	Robust	WLS	Robust	WLS	Robust	WLS
$Leave_t$	0.0353	0.0379	0.6725**	0.5235	0.3598	0.2909
	(0.0676)	(0.0910)	(0.2813)	(0.3727)	(0.4219)	(0.4905)
$Leave_t^2$	-0.0215	-0.0264	-0.7836**	-0.6267	0.0339	0.092
	(0.0768)	(0.1048)	(0.3732)	(0.4971)	(0.3680)	(0.5055)
$Leave_{t-1}$	0.037	0.0225	-0.7914***	-0.5471	-1.0977**	-1.0309*
	(0.0952)	(0.1137)	(0.2816)	(0.4128)	(0.5115)	(0.5626)
$Leave_{t-1}^2$	0.0082	0.0172	0.6396*	0.3758	1.1325**	1.0567*
	(0.1052)	(0.1306)	(0.3812)	(0.5447)	(0.5308)	(0.6009)
$Leave_{t-2}$	-0.032	-0.0165	0.1101	-0.0708	0.4962	0.4832
	(0.0854)	(0.0914)	(0.3434)	(0.3275)	(0.4722)	(0.5009)
$Leave_{t-2}^2$	-0.0214	-0.0311	-0.289	-0.0932	-0.4667	-0.4653
	(0.0939)	(0.1039)	(0.4050)	(0.4304)	(0.4965)	(0.5552)
F-test (p-value)	0.501	0.784	0.000***	0.073*	0.039**	0.199
Observations	490	490	505	505	490	490
R-squared	0.971	0.976	0.986	0.981	0.981	0.944

Chapter 4

Compete for a better future? Effects of competition on child care quality

4.1 Introduction

Across OECD countries, privatization of welfare state functions has been a common trend over the last decades. Multiple private providers are expected to respond in an efficient way to differentiated consumers preferences. Relevant examples in this respect are the energy and health insurance markets. In line with this overall trend, the Dutch child care sector was completely reorganized by the introduction of the 2005 Child Care Act. As a result of the change towards a demand driven financing system, publicly provided child care in the Netherlands disappeared. Instead only private providers are now operating and competing in the child care market (Noailly and Visser, 2009).

Yet, child care is not a purely private good. Child care publicly supported to increase female employment. Multiple intervention studies indicate that especially high quality child care has positive long-term development effects (Melhuish et al., 2008; Heckman et al., 2010; Chetty et al., 2011). The child care market does not only outsource care for working parents but also forms the early part of education (Baker, 2011). Due to a potentially large positive externality from development effects, whether a free market can provide high quality child care becomes a crucial issue in designing the child care market. This is especially relevant in the child care market as the claims of markets' efficiency and competition's ability to improve quality is based on well informed parents. If parents are unable to distinguish between high and low quality child care, a private market may instead lead to competition on prices and a race to the bottom in quality.

This chapter analyzes the impact of competition on child care quality in the Dutch market. The impact of competition in the more traditional education institutions such as secondary schools has been a long standing question. However, child care quality is difficult to observe for parents, since there are no obvious quality indicators such as graduation rates or grades. Consequently, the effects of competition may differ between secondary schools and child care centers. Whether market competition has the socially desirable effect of improving quality in child care markets is thus a separate and primarily empirical question.

The main data source used in the analysis is Pre-Cool, a survey of child care centers in the Netherlands. The Pre-Cool survey provides data on process quality of the participating child care centers. Process quality measures are designed to capture the experience a child has in the classroom by assessing child-caregiver interactions. Process quality data is collected by trained observers who visited each center to assess classrooms. The Pre-Cool also includes a survey of the center managers' which includes questions on structural characteristics such as the centers' age and size. Using data provided by Statistics Netherlands, we proxy the level of competition a center faces by the number of daycare centers around it. To overcome any potential endogeneity problems, the competition variable is instrumented using the density of primary schools within the same area. The lagged density of births in the neighborhood is introduced as a secondary instrument to test the robustness of the results.

Our results show that competition has a significantly positive, but modest effect on child care quality in daycare centers. These results are consistent across different instruments and do not change when price is taken into account. Some center characteristics also have significant effects on quality; older and smaller centers tend to have higher process quality scores. In line with the results of Blau (2000), classroom variables such as the number of staff and children have insignificant effects on process quality.

The main contribution of our study is to extend the analysis of the impact of competition from later stages of schooling to child care in early childhood. Perhaps partly because of the difficulty of collecting reliable quality indicators, there are no previous studies on the effect of competition on child care quality that we are aware of. In contrast, the impact of competition on the quality of education in secondary schools has been empirically studied at various levels. The results indicate a positive effect both at the micro and cross-country levels, although the size of the effect tends to be modest (Belfield and Levin, 2002; Sandstrom and Bergstrom, 2005; West and Woessmann, 2010).

The remainder of the chapter is structured as follows. In the following section, the institutional characteristics of the Dutch child care sector are discussed. Section 3 provides a theoretical basis to interpret the role of competition within the Dutch child care sector. Sector 4 details the econometric issues encountered and describes the IV method applied. Section 5 summarizes and describes the data available. Section 6 presents the results. Section 7 concludes.

4.2 Child Care in the Netherlands

Prior to 2005, the Dutch child care sector consisted of locally subsidized, employer financed and privately financed centers, each with their own financing structure (OECD, 2002). The Child Care Act of 2005 privatized the entire daycare market and all parents now receive a subsidy from the government for their expenditure on formal daycare up to a set hourly price. By introducing a nationally organized demand driven financing system, the 2005 Child Care Act ensured that all parents have access to same subsidies and consequently pay similar net prices that differ only by their income and by the different gross prices charged by the centers. The underlying assumption in the shift towards private providers is that price-quality ratio will improve if providers efficiently respond to parental preferences. Nevertheless, the potential for a drop in quality as a result of competition is recognized. Therefore regulations are set up through negotiations between child care providers and parental organizations. Regulations are placed on structural quality indicators such as staff-to-child ratios and caregiver qualifications. Monitoring for compliance with the regulations are handled by the municipalities.

The price cap on the subsidies, which was €6.36 in 2012, effectively places a soft cap on the prices in the market and limits variation. Since the portion of the hourly price above €6.36 is paid in full by the parents, any increase above the government cap leads to a very large net rise in what parents pay. The financing system is essentially similar to the voucher system that is often suggested for primary and secondary schools (Friedman, 1997), with the clear difference that parents only receive subsidies if they choose to use a daycare center, while schools are mandatory. Supply and availability has increased rapidly since 2005. Further increases in subsidies in 2007, despite the cutback in 2009, has led to the 2012 situation where nearly 60% of children under 4 in the Netherlands receive formal child care (Bettendorf et al., 2012).

The rise in child care use following the Child Care Act has been accompanied by a steep decline in observed quality of Dutch child care according to developmental psychologists working within the Dutch Consortium of Child Care Research (NCKO) (Vermeer et al., 2008). Using process quality instruments that measure child-caregiver interaction, NCKO researchers find that quality in Dutch child care centers has dropped from 5 to 3 on a scale from 1 to 7 between 1995 and 2008. The most recent study in 2012 show that the quality levels have stabilized, but did not rise back to its previous levels (NCKO, 2013). The results are interpreted as a decline from above average quality to below average. Lower process quality is observed despite continued regulations on structural characteristics of child care such as staff-to-child ratio and staff qualifications. The question remains whether the drop in quality can be attributed to the introduction of market forces.

4.3 Theoretical Framework

Most parents use child care that is nearby. As a result, the market for child care is not uniform across a country and is instead composed of many smaller local markets each serving an area with a small radius (Blau, 2000; Cleveland and Krashinsky, 2009). The geographical limitations of the child care market inevitably introduces differing degrees of competition for centers in different areas. The fundamental question in this chapter is thus not whether imperfect competition exists in child care but whether competition has an impact on process quality.

The standard reasoning on the potential impact of competition on efficiency or productivity is that firms are forced to become more efficient to survive against their competitors. With regards to efficiency, competition can be seen as unambiguously positive. In case of child care quality, the existence of any effects from competition is more ambiguous. The main issue is about the observation and processing of information about quality by the consumers, in this case the parents. Parents may be unable to distinguish between high and low quality child care, especially in terms of process quality. Using data from the United States, Mocan (2007) finds that parents in the child care market are weakly rational and do not use all the available information in making their decisions. This leads to a market with both information asymmetry and adverse selection. Even if parents had information about process quality levels, they may remain insensitive to process quality and focus on other aspects of child care such as prices and flexibility (Plantenga, 2012). Blau and Hagy (1998)'s finding of a small elasticity of income for structural quality seems to be consistent with information asymmetry in the market. Without parents explicitly opting for higher quality, competition is not likely to have any impact. In the Dutch market, the impact of competition is further limited because of the regulations on structural quality indicators such as staff-to-child ratios and teacher qualifications. Using a panel dataset of child care centers, Hotz and Xiao (2011) report that such quality regulations in the child care market appear to improve quality in the United States, even though they result in a smaller sector size.

In a market in which structural characteristics are regulated, an additional mechanism through which competition can have an effect can be found in the literature on managerial slack (Nalebuff and Stiglitz, 1983; Schmidt, 1997). Partially based on an earlier study by Leibenstein (1966), the managerial slack hypothesis predicts that imperfectly monitored managers and staff who are employed in an uncompetitive market can slack, ensuring that the firm survives but not providing the effort that they would have, had they been employed in a more competitive market. This hypothesis does not exclusively refer to the manager's effort. Caregivers may also have lower effort in markets where the managers have no incentive to monitor or replace employees with poor performance levels.

The managerial slack hypothesis in the Dutch daycare market with its limited price variation and structural regulation can be shown formally in a model with two players, the firm and the manager. Assuming that there is free entry into the market m for center j, profits Π can be set to equal 0 in the equilibrium. We make a strong simplification and assume that costs for the firms are exogenously given and equal for all firms in the Dutch setting because of the structural quality regulations and the larger labor market which results in a common wage rate. To break even given the government set price p, the center needs to attract sufficient number of children by offering quality Q^*. Since for each market, the competition level ε_m and the demand characteristics D_m are different, the equilibrium quality level is given by the function $Q^*(D_m, \varepsilon_m)$, which is increasing in both D_m and ε_m. Centers in areas where parents are less interested or informed about process quality will have a lower quality requirement for survival. Quality itself is produced through two inputs $Q = s^* + e$, the structural factors s^* and managerial effort e. To ensure an interior solution at the equilibrium Q^*, we assume $Q^* > s^*$. Managerial effort is determined by the manager's utility function. Although there is no monitoring, the manager gets w only if the company survives by having profits equal to or greater than 0. Since $\Pi > 0$ does not change the manager's wage, the manager has no incentive to increase his effort beyond $\Pi = 0$.

$$U^m = w - e \text{ if } \Pi \geq 0 \text{ or } U^m = 0 \text{ if } \Pi < 0 \tag{4.1}$$

Assuming that the function $Q^*(D_m, \varepsilon_m)$ is additively separable and linear for ε_m, managerial effort e^* needed to reach the break even point can be easily determined.

$$Q^*(D_m) + \varepsilon_m = s^* + e^* \tag{4.2}$$

$$e^* = Q^*(D_m) + \varepsilon_m - s^* \tag{4.3}$$

The presented formalization is simple but clarifies the two main issues in the child care market. First, equation (4.3) shows that effort and quality rises with competition. Any surplus from a local monopoly is absorbed by the manager since the firm cannot monitor effort and adjust wages accordingly. At high levels of competition where $e^* < w$, the manager has no incentive to put in any effort and would prefer the 0 pay-off rather than a negative pay-off. Hypothetically, high levels of competition can even have a negative effect on quality. Second, the demand characteristics matter. In markets where parents do not demand higher process quality, there is less incentive to put in the effort required to supply it. Of course, many complications are left out of the model. While price variation is low, it does exist in the Dutch child care market. Similarly, centers can opt to have structural quality above that required by regulation or manage lower costs while complying with the regulations. Although our main hypothesis is that competition and process quality are positively related, the impact of competition on process quality remains a fundamentally empirical question.

4.4 Empirical Methodology

The method of estimation for the effect of competition on quality in class i of center j located in market m would ideally be a linear OLS regression such as equation 4.4, where x_{ijm} are class specific, z_{jm} are center specific and M_m are market or area level characteristics and v_{ijm} is the error term. Considering that observations from the same center are likely to have correlated unobservable characteristics, standard errors clustered at the center level need to be estimated for equation (4.4). The main interest is on variable ε_m, which is assumed to capture the effect of competition. Previous studies on competition and quality or firm performance have used variables such as market power, market share or concentration (Nickell, 1996). In the case of service sectors such as health care or schooling, the competition a firm faces is usually measured by the number of firms operating nearby. In health care, Propper et al. (2004) and Bloom et al. (2010) analyze the impact of competition on hospital quality using the density of hospitals in the area. Agasisti (2011) finds positive effects from competition on schooling outcomes to be driven by the number of schools in the area. We follow the same line of reasoning as the literature on schooling and health care and measure competition in child care by employing the average number of daycare centers within three kilometers in the area to measure competition ε_m.

$$Q_{ijm} = \beta_0 + \beta_1 x_{ijm} + \beta_2 z_{jm} + \beta_3 M_m + \beta_4 \varepsilon_m + u_{ijm} \tag{4.4}$$

The main econometric concern is a possible endogeneity problem with regard to the competition variable. In terms of the theoretical framework presented, the potential endogeneity arises from a plausible correlation between the demand characteristics D_m not only with quality as assumed, but also with competition ε_m. While we later control for average income and the degree of urbanization in the area, not all demand characteristics can be included in the regression analysis. Dual income families in urban areas may have a strong preference to use daycare regardless of quality, leading to a downward bias in the OLS estimate of β_4. Additionally, more centers may be started in areas where care quality is low in order to take over low quality centers' pupils, which would also lead to a negative relationship between the number of centers in an area and quality. Either way, there is an argument to be made for potential endogeneity issues in the ordinary least square (OLS) estimates which would place a downward bias on the estimated coefficients.

A reasonable instrument needs to be both valid, thus correlated with the independent variable, and exogenous from the error term. Competition has previously been instrumented using a proxy for the level of demand in the electricity sector (Fabrizio et al., 2007). To instrument the density of primary and secondary schools, a similarly demand side instrument is popular, namely the proportion of Catholics in the local area who historically tend to prefer private schools (Cohen-Zada, 2009). In the case of Dutch child care, number of children in the neighborhood would be the obvious choice as the demand side instrument. However, child density in the area needs to be included as an independent variable since positive shocks in the number of children can cause waiting lists in daycare centers which would hamper competition until supply can adjust. Instead, we use the density of primary schools in the area as an instrument. The density of primary schools acts as a lag of the potential demand in the area, allowing us to circumvent short-term shocks in fertility. More crucially, primary school attendance is mandatory unlike child care and omitted demand characteristics which may have an impact on quality can not have an impact on the number of primary schools needed in an area. Furthermore, as of 2009, primary schools are directed to help parents find out-of-school care. The legislation implies that there are economies of scale to having daycare centers and primary schools at the same location, which is already a common occurrence in the Netherlands. Thus, we expect that primary school density would both be related to the number of child care centers in an area and exogenous from error term in equation (4.4). The first and second stages of the resulting estimation can be written as in equations (4.5) and (4.6). In all 2SLS estimates, standard errors clustered at the center level are specified.

$$\varepsilon_m = \gamma_0 + \gamma_1 x_{ijm} + \gamma_2 z_{jm} + \gamma_3 S_m + \gamma_4 M_m + v_{ijm} \tag{4.5}$$

$$Q_{ijm} = \beta_0 + \beta_1 x_{ijm} + \beta_2 z_{jm} + \beta_3 M_m + \beta_4 \hat{\varepsilon}_m + u_{ijm} \tag{4.6}$$

The relevance of competition in the child care sector with regard to quality can be estimated using equations (4.4) and (4.6). However, to identify the complete impact of competition on quality, we need to take into account the small variation in prices in the Dutch child care sector. Although price variation is limited in the Netherlands due to the government cap on subsidies, there is some variation which remains uncontrolled for in equation (4.6). Competition may drive down prices first and only then improve quality. For example, even disregarding small differences in prices might lead to an underestimation of the casual impact of competition on the overall quality-price level. Theoretically, price itself may be affected by the level of competition and including it as a control variable in equation 4.6 would lead to what Angrist and Pischke (2008) refer to as the 'bad control' problem. In the intuitively plausible case of a negative effect on prices from competition and positive effect from prices on quality, there would be an overestimation of the effects on quality if price is added as a control variable. Rather than including price as an independent variable, we make price a part of the dependent variable by estimating equation 4.7, where quality is divided by price. Equation 4.7 thus estimates the effect of competition on the quality-price ratio that the center offers rather than the effect of competition on the quality level itself.

$$\frac{Q_{ijm}}{P_{ijm}} = \beta_0 + \beta_1 x_{ijm} + \beta_2 z_{jm} + \beta_3 M_m + \beta_4 \hat{\varepsilon}_m + u_{ijm} \tag{4.7}$$

4.5 Data

Throughout this study, we make use of two data sources. Data on child care centers' quality and characteristics are obtained from the first wave (2010-2011) of the Pre-Cool survey that is being conducted in the Netherlands. In addition, information at the neighborhood or municipality level for income, population, child care center and school density are retrieved from the Dutch Statistics (CBS). These two data sources are supplemented by information obtained from the child care centers' official websites and municipalities' inspection reports on the centers.

Unlike schooling where quality related variables such as graduation rates or grades are easily observable, child care quality is intrinsically more difficult to judge. The Pre-Cool survey includes observations by trained personnel who rate the process quality in a classroom according to the Classroom Assessment Scoring System (CLASS) used by developmental psychologists (Mashburn et al., 2008; Howes et al., 2008). Similar process quality instruments have been utilized by economists as well (Blau, 1997). A classroom is graded based on its performances in factors belonging to two large domains: emotional support and instructional support. The emotional support domain is constructed using four dimensions that classroom observers give grades on: positive climate, teacher sensitivity, behavior guidance and regard for child perspectives. The instructional support domain is made up of three dimensions: facilitation of learning and development, quality of feedback and language modeling. All dimensions within the domains are graded on a scale from 1 to 7, with 1 as the lowest and

Table 4.1: Average Process Quality in Pre-Cool Daycare Centers, 2010-2011

Process Quality Measures	**Mean**	**Std. Dev.**	**Min.**	**Max**
Emotional Support	4.993	0.885	2.250	6.750
Instructional Support	3.077	1.077	1	6

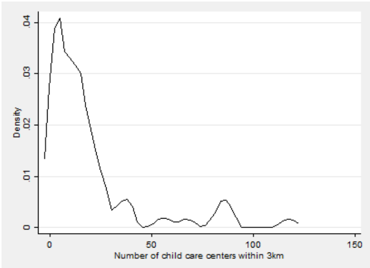
7 the highest. [1]

There are process quality observations from 65 daycare centers in the Pre-Cool sample. Multiple observations are made per center, allowing observers to rate both different groups and activities. Due to missing data issues, we make use of 294 observations from 40 daycare centers in the regressions. Table 4.1 presents the averages and standard deviations of quality measurements in all daycare centers within the sample, showing the state of child care quality in the Netherlands as a whole. Overall, process quality is above the average level of 4 for emotional support around 5. On the other hand, the instructional support scores are below average, around 3. Compared to previous studies using CLASS, child care quality in Dutch centers appears to be slightly below Finnish and above or equal to American centers. Howes et al. (2008) find an average emotional support score of 5.29 and instructional support score of 2.20 in the United States while the average of the scores reported by Pakarinen et al. (2010) in Finland are 5.19 for emotional support and 3.97 for instructional support.

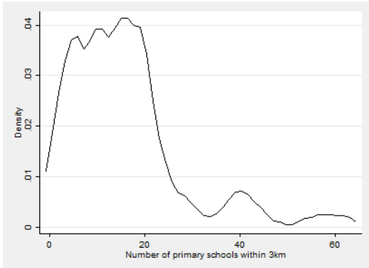
Directly taking the average of the various dimensions of instructional and emotional support domains ignores potential consistency problems between the measures and diminishes the variation between centers' quality levels. We make use of factor analysis to generate scores for emotional support and instructional support domains. In addition to the two domain variables, we construct an overall quality measure using all quality dimensions. The constructed summary variables from principal component analysis show a correlation well above 60% with all but one of the dimensions listed under both emotional support and instructional support. The exact factor loadings are presented in the Appendix. After normalization, the constructed summary variables have a mean of 0 and a standard deviation of 1.

Dutch Statistics provides data on the number of daycare centers within three kilo-

[1] More details on Pre-Cool observations and dimension scores can be found in Leseman and Slot (2013). Constructed variables and basic results of the Pre-Cool survey are to be made publicly available through the Dutch Data Archiving and Network Services (DANS). More information on DANS can be found at http://www.dans.knaw.nl/en, details of the Pre-Cool project is available in Dutch at http://www.pre-cool.nl/.



(a) Daycare Centers



(b) Primary Schools

Figure 4.1: Kernel Density Figures for the Number of Schools and Centers in the Neighborhood

meters of any neighborhood and the most commonly found 4 digit postcode in that neighborhood.[2] The number of centers variable is matched to the centers from the Pre-Cool survey using the centers' own postcodes and the most commonly found postcode in the neighborhood. In some cases, this meant that the average of the number of centers within 3 kilometers had to be used since there were multiple neighborhoods with the same 4 digit postcode as the center. For a few centers from Schiedam and Rotterdam, we used the average of the neighbourhoods with the most commonly found postcode that was closest to the centers' postcodes. This is only applied in cases where there was a neighborhood with a 4 digit postcode with a value below or above 1 of the centers' postcode. The same method was followed for the primary school density in the area, which is measured using the Dutch Statistics variable that provides the average number of primary schools within three kilometers in a neighborhood. The kernel density figures showing the distribution of these two variables are shown in figure 4.1.

The regression analysis in section 6 includes a number of additional control variables. Regressing quality on the density of daycare centers gives a coefficient close to 0 since there are a number of variables that are correlated with both. Number of children and adults in the classroom are included as classroom controls. The survey includes 14 activity categories for the activity but their inclusion can cause issues in the degrees of freedom for the clustered standard errors in some of the 2SLS estimations. Nevertheless, when we do include them in the OLS specifications, the effects

[2] As a robustness check, we tried the number of centers within five kilometers as the competition variable. There were no significant changes in the results, though some of the five kilometer data is from 2010. OLS estimates are larger while 2SLS estimates are smaller than the three kilometer variable.

of competition only become slightly smaller. Activities that were observed similarly have a significant effect in all observations. Clearly, whether children were eating or playing affects the CLASS scores in both instructional and emotional support domains. Competition can influence observed activities if higher quality results in more educational activities. The number of children and staff in the classroom are not values provided by the center but by the observers who were filling out the CLASS scales. Even though staff-to-child ratios are regulated in the Netherlands, there were still some variations in the number of adults present when the observations for process quality were made. However, dropping the number of children and adults from the specifications had little impact on the estimated effect of the competition variable on daycare centers' quality.

At the center level, controls for center type, number of groups in the center, proportion of non-Dutch caregivers, center age in years and the holding company' size are added. All center level variables are based on a survey filled by the center's managers. Center type is defined by a binary variable, with 1 indicating a nonprofit firm and 0 a for-profit firm. Some missing cases were completed using information from information found online. A few of the centers' online information is not completely clear, but dropping this variable does not change the results for competition. The variable for the proportion of non-Dutch teachers is linear and discrete from 0 to 10. A value of 5 would mean that the manager thinks half the caregivers are from a minority background, at 10, the corresponding proportion is 100%. Center age and holding company' size are both linear discrete variables and increase categorically. The holding company's size is measured by the number of child care centers owned by it. The full list of categories can be found in table 4.2. Two other center level controls were added but are excluded in the final analysis: proportion of minority children and total staff FTE. Adding these two controls leads to a sample of 32 centers instead of 40 without changing the results much except for some 2SLS estimates where the effects of competition become weaker. Including the proportion of minorities in the municipality in place of these variables actually leads to slightly stronger effects from competition.

Price information for 2012 and 2013 was collected from the official websites of the daycare centers. Price offers change depending on the daily, weekly and yearly use that the parents agree to. The prices on full-time child care were retrieved, with any existing offers for different number of days per week averaged. To harmonize data from different years, prices are assumed to have risen at the same rate as the subsidy cap which rose from €6.36 to €6.46 between 2012 and 2013. Most prices are in fact very close to the subsidy cap, with the average price in the resulting sample at €6.57.

At the area level three further controls are added at the municipality level: average income of the population in 2010, the number of children per kilometer square in 2011 and whether the municipality is defined as having hardly any or no urbanization by Dutch Statistics. To control for income, average income per person in the municipality in which the center is located is used. The 2011 data is missing for a few municipalities. Instead, we used the income data for 2010. The child density variable defined as the number of children per kilometer square is extracted at the municipality level. The municipality areas are larger than the neighborhood data used for the density of schools and daycare centers. Nevertheless, there are over 400 municipalities in the Netherlands, suggesting that any effects from these variables may be captured at the municipality level. Summary statistics for the main variables used in section 5 are presented in table 4.2.

Table 4.2: Summary Statistics of Dutch Daycare Centers

	Mean	Std. Dev.	Min	Max
Groups Controls				
# of children	9.72	3.06	2	23
# of adults	1.99	0.79	1	4
Center Controls				
# of groups	4.44	2.00	1	10
Firm size	3.32	1.11	1	4
Firm age	4.3	0.93	2	5
Non-Dutch Teachers	2.25	2.13	1	8
Hours open	10.43	1.02	1	9
Nonprofit foundation	0.46	0.5	0	1
Prices	6.57	0.27	5.41	6.89
Area Controls				
Income (x1000 euros)	14.31	1.12	12.9	17.9
Child density (x100)	1.30	1.14	0.06	3.88
Low urbanization	0.18	0.38	0	1

4.6 Main Results

Table 4.3 presents the OLS estimates of equation 4.4 for the two process quality domains and the overall quality score defined in the Classroom Assessment Scoring

System (CLASS). Competition is measured by the average number of centers within 3 kilometers. The variable is in log form for easier interpretation and a stronger effect in both OLS and 2SLS estimates, which indicates that the relationship between competition and quality is concave. The OLS estimates indicate that for both emotional support and instructional support, the relationship between competition and quality is positive and significant but not very large. A doubling in the child care density within 3 kilometers is correlated with higher quality of about one fifth of a standard deviation in these two domains. Given that the average number of centers within 3 kilometers in our sample is 22.64 (the average is 14.8 when we exclude observations from Amsterdam, Rotterdam and the Hague), the increase from an extra center opened in the area is fairly small. The corresponding increase is slightly larger in the overall quality measure. The positive relationship between competition and quality is consistent for all three measures.

As discussed in section 3, we also estimate the impact of competition by instrumenting the number of daycare centers within 3 kilometers. Just as the number of daycare centers, the number of schools are used in log form. Higher numbers indicate a higher primary school density. The number of schools is of course highly correlated with the number of daycare centers in a neighborhood and the F-test on the instrument in the first stage equation indicates an F-statistic of 74.88. According to the Monte Carlo simulations of Stock and Yogo (2002) our instruments are not weak. The first stage estimates are presented in the Appendix. We estimated all models using both Limited Information Maximum Likelihood (LIML) and 2SLS to ensure consistency and the LIML results seem to be the same as 2SLS estimates.

The results of the 2SLS estimates can be seen on the right side of table 4.3. The child care center density variable is once again significantly positive in instructional support as well as the overall quality measure. The coefficient is about the same as the OLS estimates in all 2SLS. The most significant difference is in the emotional support domain where the 2SLS coefficient for the competition variable is less significant. Whether there is any bias due to a correlation with omitted demand characteristics or companies tending to open new centers around lower quality centers is unclear. The results for the Dutch child care sector appears to be parallel to the findings in the literature on schooling and competition. Belfield and Levin (2002) report from the survey of American studies that while the impact of competition on school quality was significantly positive, they were also rather modest. The same conclusion may be appropriate for the Dutch child care sector, where a doubling of the number of centers within 3 kilometers improves overall quality by slightly less than a quarter of a standard deviation.

In both OLS and 2SLS estimates, the controls for the number of children and the number of adults at the classroom level are insignificant. A further F-test on the number of children and adults confirms that the staff-to-child ratio has insignificant effects. At the center level, some of the control variables have significant effects both in OLS and 2SLS estimates. Center age has a positive effect while the number of groups in a center, number of hours a center is open for and the proportion of teachers from minority backgrounds have a negative effect on process quality measures. The effect of the variable with teachers from minority backgrounds may be capturing the impact of neighborhoods with high proportions of minorities. The significant effects from the center age variable suggests that experience and establishment plays a role in providing higher quality care. Larger centers that are open for longer hours tend to be worse in terms of quality however, suggesting some trade-offs between a center's flexibility and quality. Including the number of groups and the proportion of caregivers from minority backgrounds seem especially important for the effect from competition since these variables are positively correlated with the competition variable. This is most likely due to economies of scale in areas with large number of centers and the higher proportion of minority inhabitants in these areas. Conversely, excluding firm size and center age increases the effect size of competition slightly since larger firms are concentrated in denser areas.

While some center characteristics have significant effects, non-profit status is insignificant throughout which is in line with previous results in service sectors (Koning et al., 2007), but is contrary to the finding that non-profit centers provide better quality child care at least in markets with sufficient demand (Cleveland and Krashinsky, 2009). The contrary findings may be explained by our inclusion of the center age variable. Non-profit status is positively correlated with center age, which has a significant positive effect.

The structure of the error term is critical in getting interpretable results when multiple observations from a single center are included in the dataset. Fitting the same linear regression without clustered errors and ignoring the fact that multiple observations of the same center are included in the data can lead overly significant effects. Almost all the variables have much smaller standard errors if clustering at the center level is not taken into account. The number of classroom controls that are used in this study is relatively limited. The finding that their significance drops once center effects are controlled for is consistent with the findings of Blau (2000) who concludes that structural factors do not have a very strong effect on process quality once center and area fixed effects are included in the analysis.

Child density, income and degree of urbanization at the municipality level have some effects, but none of them have a significant effect in all estimations. Child density and low urbanization both have positive coefficients but neither are significant by themselves. Income has some positive effects for emotional support but is also insignificant in other regressions, which is possibly due to measurement from the error variable being based on the municipality level rather than the neighborhood level. We may be unable to capture income effects if within municipality variation of income is too large and the actual effects to center quality stem from the centers' immediate surroundings. We also included a variable for the proportion of minority inhabitants in a municipality, but this variable had little effect on the effects from competition since it is highly correlated with the degree of urbanization and center characteristics such as the proportion of minority caregivers. Effects of competition weaken if we include 4 dummies for each urban category as defined by the Statistics Netherlands, but including the proportion of minorities in that specification gives results that are similar to the main model.

4.6.1 Number of Births an Alternative Instrument

The results so far suggest that the OLS and 2SLS estimates are not significantly different when the number of schools in the area is used as an instrument for the number of daycare centers. There is however the possibility that our initial instrument, the number of schools, may not be exogenous from quality in child care centers or its relevance to the number of daycare centers may be spurious. As an alternative instrument and robustness check, we use the number of births in the neighborhood obtained from Dutch Statistics. The assumption is that neighborhoods with more births will also have more daycare centers due to higher demand. Clearly, larger neighborhoods may have more total births while having a lower child density. As such, the total number of births are divided by the surface area of the neighborhoods to obtain a birth density variable which is then used in log form. Using it in linear form gives similar coefficients, but much larger standard errors since the instrument becomes weaker. Fertility shocks and their impact on waiting lists would potentially make birth density an invalid instrument. To avoid a this endogeneity problem, data for the

Table 4.3: Determinants of child care quality

	OLS			2SLS		
	Instructional Support	**Emotional Support**	**Overall Quality**	**Instructional Support**	**Emotional Support**	**Overall Quality**
Group Characteristics						
# of children	-0.0183	-0.0038	-0.0149	-0.0178	-0.0033	-0.0143
	(0.0210)	(0.0226)	(0.0237)	(0.0196)	(0.0217)	(0.0226)
# of adults	0.0643	0.0033	0.0414	0.0592	-0.0018	0.0356
	(0.0730)	(0.0838)	(0.0848)	(0.0684)	(0.0806)	(0.0799)
Center Characteristics						
# of groups	-0.1471***	-0.1388***	-0.1710***	-0.1526***	-0.1442***	-0.1772***
	(0.0420)	(0.0417)	(0.0453)	(0.0383)	(0.0393)	(0.0425)
Firm size	0.0269	0.0904	0.0643	0.0245	0.088	0.0616
	(0.1010)	(0.1214)	(0.1253)	(0.0997)	(0.1181)	(0.1225)
Center age	0.2091**	0.2057**	0.2442***	0.2041***	0.2007***	0.2385***
	(0.0820)	(0.0782)	(0.0800)	(0.0785)	(0.0738)	(0.0751)
Non-Dutch teachers	-0.0912*	-0.1747***	-0.1550***	-0.0990**	-0.1824***	-0.1640***
	(0.0490)	(0.0475)	(0.0538)	(0.0496)	(0.0489)	(0.0549)
Hours open	-0.2250***	-0.2359***	-0.2764***	-0.2289***	-0.2398***	-0.2809***
	(0.0690)	(0.0753)	(0.0822)	(0.0702)	(0.0746)	(0.0821)
Non-profit foundation	0.0307	-0.1403	-0.0669	0.0395	-0.1316	-0.0569
	(0.1940)	(0.2319)	(0.2383)	(0.1878)	(0.2222)	(0.2289)
Area Characteristics						
Income	-0.046	0.1267	0.0448	-0.0445	0.1281*	0.0464
	(0.0680)	(0.0784)	(0.0803)	(0.0649)	(0.0752)	(0.0770)
Child density	0.0378	0.1699	0.1212	0.0379	0.17	0.1213
	(0.0900)	(0.1070)	(0.1018)	(0.0849)	(0.1055)	(0.0988)
Low urbanization	0.248	0.452	0.4226	0.3111	0.5143	0.4947
	(0.3970)	(0.3672)	(0.4335)	(0.3646)	(0.3497)	(0.4027)
# of centers (3km)	0.1602**	0.1384**	0.1838***	0.1931*	0.1708*	0.2214**
	(0.0720)	(0.0661)	(0.0667)	(0.1042)	(0.0881)	(0.1036)
# of centers	40	40	40	40	40	40
Observations	294	294	294	294	294	294
F-test instruments	-	-	-	74.88	74.88	74.88

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Center age categories: <1 year, 1-2 years, 3-4 years, 5-10 years, >10 years. Firm size categories (# of centers): 1, 2-5, 6-10, >10.

number of births are lagged two years and are from 2009 as opposed to the number of daycare centers data which are from 2011. The number of daycare centers would presumably adjust to increases or decreases in fertility rates within two years. Using the number of births from years before 2009 is not possible due to large number of missing cases.

Table 4.4 shows the results for 2SLS estimates using birth density as an instrument for the number of daycare centers. On the right side of the table, estimates using both the number of schools and birth density as instruments are shown. There do not seem to be strong evidence of overidentification problems according to the Sargan test and the F-test on the instruments are all larger than 10. The effects of competition seen in table 4.4 do not qualitatively differ from the initial findings presented in table 4.3. The competition variable is significantly positively related to child care quality in all estimates. However, the estimates using birth density as an instrument for competition show considerably larger effects from competition than those using only the number of schools or the OLS estimates. Taken together, the results indicate that the positive impact from competition on child care quality is quite robust to alternative instruments, while the predicted downward bias in OLS estimates is less obvious.

4.6.2 Competition and Quality-Price Ratio

From a perspective of child development and externalities from child development, quality of child care may be the most crucial aspect. However, parents' utility presumably depends on both prices and quality of available child care. While the impact of competition on quality is perhaps socially more relevant, the price-quality ratio would be a better measure of how competition affects the consumer surplus in the child care market. For example, if the average price falls in an area while quality is raised, the rise in the consumer surplus may be larger than that implied by the results in table 4.3. To that end, the dependent variable is reconstructed as the quality measure divided by price in euros as shown in equation 4.7. The price data are either from or adjusted to 2012. Since price information was collected after the Pre-Cool survey of 2011, there is a time lag between the remainder of the variables used in the analysis and the prices. One center had disappeared since the process quality observations were made and no price information could be found. The results for the remaining 39 centers for the determinants of the overall child care quality-price ratio

Table 4.4: Alternative instruments for estimating the impact of competition

Instrument:	Birth density			Birth density + # of schools		
	Instructional Support	**Emotional Support**	**Overall Quality**	**Instructional Support**	**Emotional Support**	**Overall Quality**
Group Characteristics						
# of children	-0.0126	0.0015	-0.0083	-0.0168	-0.0024	-0.0132
	(0.0215)	(0.0225)	(0.0243)	(0.0198)	(0.0217)	(0.0227)
# of adults	0.0011	-0.0556	-0.0313	0.0479	-0.0122	0.0226
	(0.0956)	(0.0948)	(0.1085)	(0.0719)	(0.0819)	(0.0835)
Center Characteristics						
# of groups	-0.2147***	-0.2017***	-0.2488***	-0.1646***	-0.1553***	-0.1911***
	(0.0675)	(0.0581)	(0.0716)	(0.0415)	(0.0397)	(0.0445)
Firm size	-0.0021	0.0634	0.031	0.0194	0.0833	0.0557
	(0.1146)	(0.1292)	(0.1393)	(0.1002)	(0.1187)	(0.1233)
Center age	0.1471	0.1479	0.1727	0.1930**	0.1905***	0.2257***
	(0.1062)	(0.0933)	(0.1074)	(0.0800)	(0.0739)	(0.0762)
Non-Dutch teachers	-0.1881**	-0.2650***	-0.2666***	-0.1163**	-0.1984***	-0.1838***
	(0.0846)	(0.0866)	(0.0988)	(0.0515)	(0.0530)	(0.0586)
Hours open	-0.2737***	-0.2813***	-0.3325***	-0.2376***	-0.2478***	-0.2909***
	(0.0758)	(0.0868)	(0.0929)	(0.0691)	(0.0755)	(0.0820)
Non-profit foundation	0.1396	-0.0389	0.0584	0.0589	-0.1137	-0.0345
	(0.1952)	(0.2178)	(0.2318)	(0.1834)	(0.2170)	(0.2231)
Area Characteristics						
Income	-0.028	0.1435*	0.0655	-0.0413	0.1311*	0.0501
	(0.0660)	(0.0774)	(0.0792)	(0.0641)	(0.0749)	(0.0764)
Child density	0.0389	0.171	0.1225	0.0381	0.1702	0.1215
	(0.1003)	(0.1450)	(0.1375)	(0.0829)	(0.1109)	(0.1018)
Low urbanization	1.0289	1.1796	1.3217	0.4503	0.6432	0.655
	(0.7002)	(0.7427)	(0.8395)	(0.3931)	(0.4026)	(0.4522)
# of centers (3km)	0.5669**	0.5173*	0.6521**	0.2656**	0.2380**	0.3049***
	(0.2780)	(0.2765)	(0.3222)	(0.1060)	(0.1003)	(0.1123)
# of centers	40	40	40	40	40	40
Observations	294	294	294	294	294	294
Hansen-J test p-value	-	-	-	0.107	0.104	0.095*
F-test instruments	10.41	10.41	10.41	58.58	58.58	58.58

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Center age categories: <1 year, 1-2 years, 3-4 years, 5-10 years, >10 years. Firm size categories (# of centers): 1, 2-5, 6-10, >10.

are presented in table 4.5.

Though less significant in case of the estimate using the number of schools as the instrument, the effects of competition on the quality-price ratio is in line with those for the quality levels. For all estimation procedures and instruments, there is a significant positive effect from competition on the quality-price ratio. To detect whether the introduction of prices changes the main results found in table 4.3, the coefficients can be multiplied by the average price in the sample. In case of the 2SLS estimate using the number of schools as the instrument, the coefficient is calculated (by multiplying the coefficient by the average price) to be 0.1747 for the level of quality, which is almost the same as the coefficient of 0.193 found in the corresponding estimate without prices. The introduction of prices to the analysis thus does not significantly change the estimated effect on the quality measures. The difference is also small for the estimate that uses both birth density and the number of schools as instruments. The coefficient for the quality level is given as 0.305 while the effect on quality can be calculated to be 0.369. When we tested whether price was affected by the competition variable, we found no significant effects. At least in the Dutch case, competition does not appear to result in a race to the bottom in terms of prices and the impact of competition is limited to the quality aspect.

4.6.3 (Lack of) Competition in the Playgroup Sample

While the results so far suggest a positive effect from the number of daycare centers in the area on child care quality in daycare centers, this does not necessarily lead to the conclusion that competition improves quality. Centers can benefit from spillover effects from center density regardless of competition. Alternatively, other supply side explanations such as a larger caregiver labor market in the area might account for the positive relationship between daycare center density and quality.

To further test whether competition is truly driving the results, we make use of the differences between the financing and demand characteristics of playgroups and daycare centers in the Netherlands. While daycare centers operate within a market with demand side considerations and have to attract parents, playgroups targeted towards 2 year olds are financed directly by municipalities. In addition, since daycare subsidies are only available for working parents, playgroups are used by single earner families. Unlike public and private schools which compete for the same students (Dee, 1998), the resulting degree of substitutability between daycare centers

Table 4.5: Determinants of child care quality-price ratio

	OLS	2SLS		
Instruments		**# of schools**	**Birth density**	**# of schools / birth density**
Group Characteristics				
# of children	-0.0012	-0.0011	0.0002	-0.0008
	(0.0036)	(0.0033)	(0.0036)	(0.0033)
# of adults	0.0046	0.0034	-0.0076	0.0008
	(0.0128)	(0.0119)	(0.0169)	(0.0126)
Center Characteristics				
# of groups	-0.0262***	-0.0274***	-0.0392***	-0.0303***
	(0.0068)	(0.0064)	(0.0121)	(0.0068)
Firm size	0.0099	0.0094	0.0044	0.0082
	(0.0195)	(0.0190)	(0.0221)	(0.0191)
Center age	0.0362***	0.0357***	0.0309*	0.0346***
	(0.0120)	(0.0114)	(0.0160)	(0.0118)
Non-Dutch teachers	-0.0232**	-0.0256**	-0.0486**	-0.0311***
	(0.0091)	(0.0105)	(0.0200)	(0.0113)
Hours open	-0.0431***	-0.0439***	-0.0515***	-0.0458***
	(0.0129)	(0.0128)	(0.0133)	(0.0124)
Non-profit foundation	-0.0106	-0.0096	-0.0001	-0.0074
	(0.0368)	(0.0353)	(0.0370)	(0.0346)
Area Characteristics				
# of centers (3km)	0.0266*	0.0355	0.1212*	0.0561**
	(0.0149)	(0.0264)	(0.0665)	(0.0276)
Income	0.0071	0.0076	0.013	0.0089
	(0.0125)	(0.0120)	(0.0125)	(0.0118)
Child density	0.0182	0.0191	0.0274	0.0211
	(0.0162)	(0.0159)	(0.0238)	(0.0170)
Low urbanization	0.0668	0.086	0.2709	0.1304
	(0.0723)	(0.0751)	(0.1697)	(0.0870)
# of centers	39	39	39	39
Observations	286	286	286	286
F-test instruments	-	30.88	9.02	33.06
Hansen-J test (p-value)	-	-	-	0.1056

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Center age categories: <1 year, 1-2 years, 3-4 years, 5-10 years, >10 years. Firm size categories (# of centers): 1, 2-5, 6-10, >10.

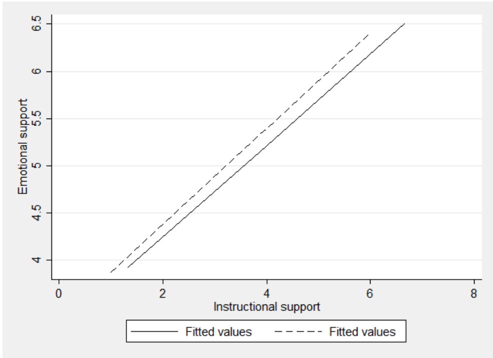


Figure 4.2: Quality in daycare centers and playgroups

and playgroups is bound to be limited. Limited substitutability implies that daycare centers and playgroups do not operate within the same market even if they are in the same neighborhood and that there is little to no competition between the two center types. Despite limited substitutability on the demand side, the inputs used in daycare centers and playgroups are perfectly substitutable. Many daycare centers apply the VVE educational curriculum that most playgroups use and the required minimum staff qualifications do not differ. Both child care types are judged on the same quality metric in the Pre-Cool survey. Although playgroups score slightly higher than daycare centers on instructional support, the average scores for instructional and emotional support are similar as shown in figure 4.2. Alternative supply side explanations for the effects of center density besides competition, such as spillover effects or a wider labor market would be expected to have effects in playgroups as well since they essentially provide the same service in a different shape and employ from the same labor pool.

We test whether the effect of center density on quality is driven by competition by fitting the same regressions shown by equations 4.4 and 4.6 to a sample of 45 playgroups. For the 2SLS estimates the log of the number of schools is the instrument. Table 4.6 shows no significant effects in OLS or 2SLS estimates on overall quality of playgroups from the competition variable except weak negative effects in two 2SLS estimates. These turn insignificant as well if the number of adults and children are omitted from the regressions. The non-significance of the effects of center density on playgroups should not give the impression that daycare centers have a higher overall level of quality because of competition. In fact, table 2 already showed that the average quality levels are remarkably similar.

Interestingly, the number of adults and children in the classroom which had no effects on daycare quality appear to have significant effects in playgroups. The significant effects may be due to the slightly larger variation in staff-to-child ratios among the playgroup sample. In addition, the lack of market competition may be prioritizing the importance of structural characteristics and the investments made within the classroom in explaining the variation in quality among playgroups.

4.7 Conclusions

Previous research in the Netherlands had found a decline in child care quality between 1995 and 2008. Although the decline in quality is most evident between 1998 and 2005, the finding raises the question of whether competition introduced by the privatization in 2005 is to blame. This paper analyzed the relationship between competition and child care quality in the Dutch child care sector using process quality measures and an instrumental variables strategy. Results indicate that there is evidence of positive effects from competition on child care quality, both in emotional support and instructional support domains of the CLASS scale. Despite worries of information asymmetry problems limiting parents' ability to demand and choose higher quality care, competition appears to improve the scores of Dutch child care centers in process quality measurements. These results are in line with the empirical literature on competition and firm performance in schooling and other sectors and supports the fundamental hypothesis that competition can improve quality and performance.

The finding suggests that the drop in quality observed the Dutch Consortium of Child Care Research (NCKO) between 1995 and 2008 is more likely to be related to the enormous growth in the supply of child care rather than competition between private centers. Dutch centers appear to compete on quality rather than in price, implying that there is little evidence for a race to the bottom. In our analysis, including or excluding price information in the analysis had no effect on the estimated impact of competition on quality.

It is worth noting that our analysis is on the effect of competition on quality within a market with structural and price regulations. These two preconditions already place child care provision into a strictly controlled and regulated market compared to most other goods and services. Further studies on the impact of competition in contexts

Table 4.6: Determinants of quality in playgroups

	OLS			2SLS		
	Instructional Support	**Emotional Support**	**Overall Quality**	**Instructional Support**	**Emotional Support**	**Overall Quality**
Group Characteristics						
# of children	-0.0299	-0.0598***	-0.0551**	-0.0316	-0.0618***	-0.0577***
	(0.0227)	(0.0154)	(0.0213)	(0.0218)	(0.0159)	(0.0207)
# of adults	0.1805**	0.2336***	0.2474***	0.2095***	0.2583***	0.2794***
	(0.0780)	(0.0714)	(0.0812)	(0.0754)	(0.0720)	(0.0800)
Center Characteristics						
# of groups	-0.0409	-0.0178	-0.0438	-0.0334	-0.0119	-0.0362
	(0.0511)	(0.0304)	(0.0477)	(0.0529)	(0.0332)	(0.0499)
Firm size	-0.0844	0.0858	-0.0038	-0.0993	0.0755	-0.0172
	(0.1447)	(0.1003)	(0.1319)	(0.1729)	(0.1101)	(0.1575)
Center age	0.1714	0.0902	0.1805	0.0762	0.0133	0.0806
	(0.2503)	(0.1424)	(0.2219)	(0.2780)	(0.1700)	(0.2572)
Non-Dutch teachers	0.0853	0.0151	0.0622	0.1259*	0.048	0.1049
	(0.0601)	(0.0351)	(0.0526)	(0.0720)	(0.0448)	(0.0663)
Hours open	-0.0032	0.0264	0.0229	0.009	0.0373	0.0371
	(0.0880)	(0.0516)	(0.0803)	(0.0962)	(0.0580)	(0.0895)
Non-profit foundation	0.426	0.3836	0.5019	0.2722	0.2554	0.3355
	(0.3193)	(0.3396)	(0.3515)	(0.3496)	(0.3343)	(0.3667)
Area Characteristics						
Income	-0.0073	0.1153	0.0634	0.0056	0.1258	0.077
	(0.1489)	(0.1066)	(0.1395)	(0.1504)	(0.1058)	(0.1414)
Child density	-0.1612	-0.3043**	-0.2803	-0.0295	-0.1968	-0.1409
	(0.1636)	(0.1505)	(0.1780)	(0.1527)	(0.1238)	(0.1509)
Low urbanization	-0.1336	0.6379**	0.2229	-0.6804	0.1896	-0.3589
	(0.5777)	(0.2970)	(0.5135)	(0.4930)	(0.3135)	(0.4495)
# of centers (3km)	-0.0098	0.1196	0.0488	-0.3320**	-0.1457	-0.2954*
	(0.1837)	(0.1223)	(0.1781)	(0.1647)	(0.1303)	(0.1636)
# of centers	45	45	45	45	45	45
Observations	290	287	287	290	287	287
F-test instruments	-	-	-	39.02	39.02	39.02

Standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Center age categories: <1 year, 1-2 years, 3-4 years, 5-10 years, >10 years. Firm size categories (# of centers): 1, 2-5, 6-10, >10.

with different structural regulations and price levels may be needed to see whether competition has a positive effect on under different governance systems.

4.8 Appendix 4A

Table 4.7: First stage estimates

	Daycare sample			Playgroups
# of children	0.0232**	-0.0142	0.0178*	0.0197
	(0.011)	(0.015)	(0.010)	(0.015)
# of adults	0.0098	0.0892	0.0038	0.0043
	(0.045)	(0.081)	(0.044)	(0.058)
# of groups	0.0579	0.0445	0.024	0.0479
	(0.044)	(0.060)	(0.039)	(0.035)
Firm size	-0.0049	0.1055	0.0199	-0.2109**
	(0.082)	(0.104)	(0.073)	(0.087)
Center age	0.0286	0.0502	0.0048	-0.2732*
	(0.075)	(0.106)	(0.060)	(0.147)
Non-Dutch teachers	0.01	0.1727***	0.016	0.0810*
	(0.040)	(0.063)	(0.035)	(0.043)
Hours open	0.1599***	0.034	0.1194**	-0.0253
	(0.048)	(0.069)	(0.047)	(0.050)
Non-profit foundation	-0.1332	-0.1578	-0.1078	-0.2293
	(0.106)	(0.212)	(0.114)	(0.261)
Income	0.2256***	0.0765	0.2360***	0.1062
	(0.076)	(0.092)	(0.076)	(0.127)
Child density	-0.1930*	-0.22	-0.2539***	0.1489
	(0.110)	(0.145)	(0.093)	(0.126)
Low urbanization	-0.2746	-0.9435*	-0.1136	-0.5112
	(0.235)	(0.500)	(0.232)	(0.306)
Log(# of schools)	1.5167***		1.3000***	1.1538***
	(0.175)		(0.163)	(0.185)
Log(birth density)		0.5556***	0.2254**	
		(0.172)	(0.094)	
Constant	-6.0914***	1.0641	-4.8593***	-0.3618
	(1.317)	(1.538)	(1.383)	(2.143)
Observations	294	294	294	287
# of centers	40	40	40	45
R-squared	0.935	0.847	0.947	0.901

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.8: Factor loadings for daycare quality measures

	Emotional Support	**Instructional Support**	**Overall Quality**
Emotional Support			
Positive climate	0.737		0.728
Teacher sensitivity	0.767		0.720
Regard for child perspectives	0.243		0.259
Behavior guidance	0.634		0.612
Instructional Support			
Facilitation of learning and development		0.686	0.688
Quality of feedback		0.744	0.696
Language modelling		0.778	0.759

Chapter 5

Cutting from the future? Impact of a subsidy reduction on child care quality in the Netherlands[1]

5.1 Introduction

Fiscal consolidation and austerity that followed the 2009 financial crisis has led to cuts in numerous welfare state services. Subsidies for child care were no exception. The 2013 budget sequestration in the United States resulted in reductions in Head Start budgets. In the Netherlands, childcare subsidies for parents using formal child care were reduced. These cuts are in contrast with the recent findings of economists of the importance of high quality child care services as an investment into future life outcomes (Heckman, 2006; Baker, 2011).

In this chapter, we consider how reductions in child care subsidies affect the quality of child care. We study the effects of a subsidy reduction in the Netherlands in 2012 on child care quality as measured by developmental psychologists. The subsidy reduction affected the entire daycare sector, which exists as a private market since 2005. Nearly half of the children in the age range 0 to 4 are in formal child care. Any effects of the 2012 reduction on the quality offered in the market may affect development and long term outcomes on this large group of children.

Our quasi-experimental identification strategy relies on the two-tiered child care

[1] I would like to thank Paul Leseman for his contribution in this paper as a co-author.

system in the Netherlands, where private daycare centers and publicly funded playgroups co-exist. Playgroups were unaffected by the subsidy reduction and serve as our control group while daycare centers make up the treatment group. A difference-in-differences (DD) model is employed for the baseline estimations. The results from the linear DD models are supplemented by estimates using synthetic control, changes-in-changes and recentered influence function models (Athey and Imbens, 2006; Firpo et al., 2009; Abadie et al., 2010). The latter two non-linear estimators also allow for the estimation of heterogeneous effects on the different quantiles of the quality distribution. The main data source is the Pre-Cool survey, a two-wave, geographically representative survey of child care centers in the Netherlands. The dataset includes relatively scarce quality measurements and has a panel structure with most centers visited in both waves. One wave of the survey was collected in the months before the cut in subsidies and one after, allowing for a straightforward estimation of the effects. The primary interest of the survey is process quality of Dutch child care centers. Process quality can be broadly defined as measuring the quality of children's experiences in classrooms, particularly with regards to social and cognitive development (Blau, 2000). It is measured through observations by trained personnel of centers' classrooms according to the Classroom Assessment and Scoring System (CLASS), which is a standardized assessment tool designed to measure process quality.

The results show a decline in child care quality that is more pronounced and significant in the middle of the quality distribution. The larger effects in the middle of the distribution is consistent with the larger reductions in subsidies for middle and higher income families. The average treatment effects are consistent across a variety of specifications while quantile effects appear to be more sensitive to the assumptions made. While the non-linear changes-in-changes and recentered influence function methods give similar results, the linear quantile OLS estimator seems to differ.

Only a few studies analyze the link between spending and quality of child care. Johnson et al. (2012) have studied the effect of subsidy receipt on the quality of child care purchased for a cross-section of 4 year old children in the US and found a positive relationship. Their study identifies the effect of subsidy receipt by comparing the quality of child care used by parents receiving subsidies and families that are eligible for subsidies but do not receive them and controlling for socioeconomic factors. A similar relationship is studied by Herbst and Tekin (2010), who find a negative effect from subsidy receipt on child development measures. However, identification of the impact subsidies may have on quality is complicated in case of countries where there is no difference in eligibility and subsidy rates for parents with same income and working hours. The Dutch child care system may be suitable for identifying effects of subsidies on quality since there exists a type of child care that are not funded through the standard subsidies. Collection of process quality information before and after the subsidy reduction in both daycare centers and playgroups within the Pre-Cool survey provides an opportunity to identify the link between child care subsidies and quality.

The outline of the paper is as follows. The following section discusses literature on child care spending and quality as well as some of the potential links between child care subsidies and quality. Section 3 describes the context of the subsidy cut and the child care market in the Netherlands. Section 4 introduces the data and empirical strategy used. Section 5 presents the linear DD methodologies and their results. Section 6 presents the non-linear models and their results. Section 7 concludes.

5.2 Child care quality and subsidies

A substantial body of literature studies the relationship between child care and child development. Findings from case studies in the U.S. such as the Perry High-school and STAR have indicated a positive impact from early childhood education on later in life employment, wages and crime rates (Heckman et al., 2010; Chetty et al., 2011). However, these results do not appear to apply to reforms with a wider scope such as those in Canada and Denmark, where child care expansions have led to worse child outcomes in terms of well-being and non-cognitive development (Baker et al., 2008; Datta Gupta and Simonsen, 2010). Longer run effects in comprehensive child care reforms have been found to have some benefits in Norway by Havnes and Mogstad (2011b). They find higher education and income among lower income cohorts born after an expansion in subsidized child care. A large body of evidence for a positive relationship between formal child care participation and children's cognitive development has also been produced by developmental psychologists (Bradley and Vandell, 2007). However, the causality of the positive relationship between cognitive development and child care found through OLS or fixed effects estimators is questioned by evidence from instrumental variable estimates provided by Bernal and Keane (2011) and Herbst (2013). These studies using exogenous variation in the timing of child care, such as the low participation in child care during summer months in

Herbst (2013), as instruments and find a negative effect on child development from attendance to formal child care. Furthermore, the longer-term findings of Havnes and Mogstad (2011b) do not apply to children from higher income families. Herbst and Tekin (2010) also find a negative effect on child cognitive and non-cognitive development from subsidy receipt for formal child care.

The mixed evidence regarding the relationship between child development and the use of formal child care suggests that there is a mediating factor that shapes the direction of the effects formal child care investment has on child development. Quality of child care is the natural culprit to examine but is typically treated as an unobserved variable, most likely due to data constraints. The studies that analyze the relationship between quality of child care and development generally find positive effects from quality. According to Chetty et al. (2011), having experienced teachers or a smaller class size has led to higher earnings in later life for students in the STAR study. Studies using process quality measures of child-caregiver interaction consistently find that child development is positively affected by high quality child care (Duncan, 2003; Peisner-Feinberg et al., 2001). Overall, the existing literature suggests an ambiguous relationship between the use of formal child care and child development and a positive relationship between the quality of child care and child development. The missing link from a policy perspective appears to be how governments can affect quality. The instruments that are typically available to the governments are so-called structural quality variables such as staff to child ratios and staff qualifications, and subsidies paid to parents or centers. Hotz and Xiao (2011) estimate the effects of US state regulations regarding child-to-staff ratios, group sizes and staff qualifications on child care quality and market size. Their findings indicate that child care regulations reduce the size of the child care market, but improve quality. However, the impact of subsidies on quality is largely unknown.

Just as investments in child care services are made to increase the use and availability of child care, the cut in Dutch child care subsidies that this chapter analyzes can be envisaged as causing a negative demand shock in the child care market. Havnes and Mogstad (2011a) find that the expansion of subsidized child care in Norway had little effects on maternal employment because decreases or increases in formal care accessibility lead to substitution towards or from informal child care. Similarly, Bettendorf et al. (2012) find that higher subsidies in the Netherlands resulted in a switch from informal to formal child care with minor effects on female employment. In the same vein, we may presume that the subsidy cuts lower the demand for formal child care prices, without a corresponding decrease in labor force participation. However, there is no prior evidence as to how subsidy cuts affect child care quality.

The impact of a change in subsidies on quality depends on what parents know. Parents have been found to value convenience and prices over quality and may have limited information on centers' quality (Mocan, 2007; Kim and Fram, 2009). Centers may then cut costs and lower quality in order to compete on prices. On the other hand, if parents have perfect information and foresight about child care quality and its effects, they may be willing to accept higher prices to avoid reductions in quality. Furthermore, regulations on caregiver qualifications and other structural factors may limit the extent to which quality can be reduced. If the regulations encompass all factors that can affect process quality and are sufficiently strenuous, quality at the market equilibrium would remain unchanged.

Treating the national child care market as one homogenous market would be a mistake given the local character of most service markets including child care. In thick markets where demand is high, price elasticity of child care use is likely to be lower than in thin markets where subsidies may cause a larger shift in demand. Cleveland and Krashinsky (2009) have found that non-profit child care centers that are expected to provide higher quality care are only able to do so in thick markets where there is sufficient demand to pay premiums for higher quality child care. Centers operating in thin markets where price elasticity is high would be more sensitive to changes in child care subsidies and are likely to react to a subsidy cut by lowering costs and quality to maintain acceptable prices.

There are multiple other mechanisms through which subsidies can influence child care quality. If competition has a positive effect on child care quality (as it does on schooling, e.g. West and Woessmann (2010)), centers shutting down as a result of lower demand can also decrease competition and parental choice, resulting in lower quality. Positive effects on quality are also plausible. A smaller market can raise the average quality of child care centers. Centers that provided low quality care in the first place should be the ones losing customers first, which would raise average quality. Possible imperfections in the child care market generally make it difficult to give apriori predictions about the effects of policy changes.

5.3 Child care in the Netherlands

The structure of the Dutch child care sector is central to our identification strategy. Formal child care centers in the Netherlands can be divided into daycare centers (*kinderdagverblijf*) and playgroups (*peuterspeelzaal*). Daycare centers are typically used by dual-income families and can cover enough hours for full-time employment.[2] Playgroups are generally used for shorter periods of time: between two to four half days a week. Both center types essentially provide the same child care service in terms of quality, but for different groups and for different hours.

Daycare centers operate in a private market and parents are free to choose the daycare center they prefer. Child care subsidies are paid directly to parents, meaning that the demand side is subsidized rather than the supply side. Subsidies are paid up to an hourly price that is adjusted each year and depend on income and the number of children of the household in daycare. In the period between 2005 and 2008, the child care sector was boosted through increases in subsidies that effectively cut prices by half for parents (Bettendorf et al., 2012). These increases were later reversed to some extent as the subsidies were reduced most recently in 2012. The change in subsidies that took place in 2012 can be seen in figure 5.1. Subsidies were cut across the board for the first child by between 2 to 5 percentage points and subsidies for the care of a second child were reduced by more than 10 percentage points depending on income. These subsidies are paid for a set maximum hourly price. The portion of the price that is above the maximum does not factor in the subsidy calculation. In addition to the reduction in subsidies, the maximum hourly price was not increased from €6.36 in 2012 while the average price in the child care market continued to rise from €6.32 to €6.45 (SZW, 2013). The rise in prices without a corresponding increase in maximum hourly price implies that there is on average €0.13 extra that parents have to pay for which they do not receive any subsidies.

Appendix 5A shows in detail the changes in net cost of monthly daycare for different family configurations, income and number of children in daycare. The increases in net monthly costs are around 15% for parents with a single child and over 25% for parents with two children in daycare. The cuts are larger in absolute terms for the higher income groups. Our hypothesis that the subsidy reduction may have

[2] Subsidies are only paid if both parents are working.

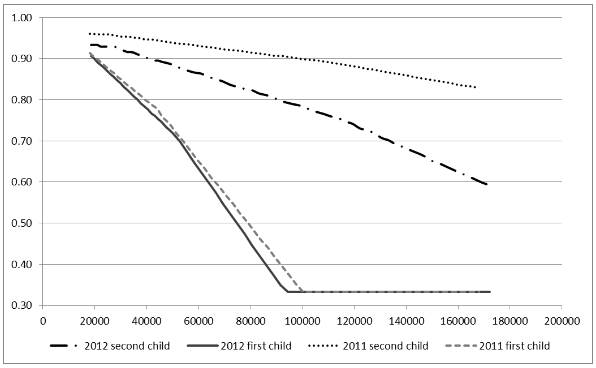


Figure 5.1: Subsidy rates for first and second children (proportion)
Source: Tax Office

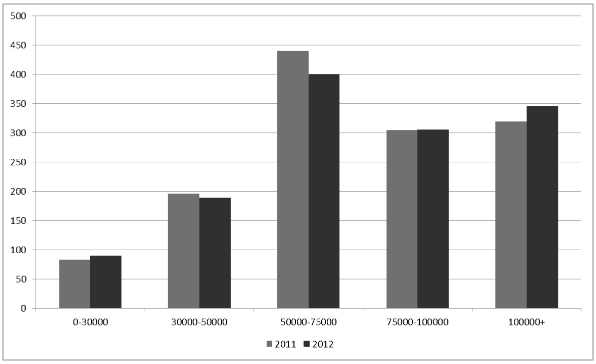


Figure 5.2: Incomes of families with one child <18
Source: Statistics Netherlands

led to a negative demand shock appears to be consistent with the figures in table 5.1. 2012 is the first year since the 2005 Child Care Act in which hourly daycare prices rose less than the core inflation rate. In line with a negative demand shock from the subsidy cuts, the number of children in daycare also declined for the first time by 3.5% after a rapid rise between 2008 and 2011 of approximately 20%. Ministry of Social Affairs figures also show that the average hours of care decreased by 5%. Playgroups are funded by municipalities with minor parental contributions and playgroup use is not subsidized on the demand side. While playgroups may also be affected by the recession and general austerity in the Netherlands, these effects would have been felt in the daycare center as well regardless of the subsidy cuts. We thus expect playgroups to serve as a valid control group to test the impact of the subsidy reduction.

Both daycare centers and playgroups are regulated in terms of structural quality factors such as child to staff ratios and space specifications. These regulations are monitored through different channels. Daycare centers' are inspected by municipalities for whether or not they confirm to the quality regulations agreed upon between parental organizations and daycare providers. Similarly, playgroups are also inspected by municipalities but their regulations are set by national law. Both center types need to pass the inspection of Municipality Health Service (GGD): daycare centers in order for the parents who use the daycare center to be eligible for subsidies and playgroups in order to receive funding.

Table 5.1: Child care market since 2005

	Average price	**Price inflation**	**Core inflation**	**Number in daycare (x1000)**
2005	€5.34		2.04%	
2006	€5.45	2.06%	1.00%	
2007	€5.65	3.67%	1.87%	
2008	€5.81	2.83%	1.94%	257
2009	€5.97	2.75%	1.11%	279
2010	€6.16	3.18%	1.93%	305
2011	€6.32	2.60%	2.38%	322
2012	€6.45	2.06%	2.90%	311

Source: Dutch Statistics, Ministry of Social Affairs

5.4 Data and methods

The data on child care quality in the Netherlands comes from the longitudinal Pre-Cool survey of Dutch child care centers, parents and children. The Pre-Cool survey consists currently of two waves, one collected in 2010 and 2011 and the other in 2012. The primary purpose of the dataset is to track the development of Dutch children. Quality information was collected from the child care centers that the children in the study attended.[3]

The unit of analysis in our study is centers' groups. The Pre-Cool survey involved sending trained observers to measure the quality of classrooms in each center. The average observation period was about 20 minutes for each classroom and multiple observations are made for each center. The full sample consists of 166 child care centers but several centers need to be dropped due to missing data issues. Furthermore, 15 of the centers were not included (or had missing data issues) in the second wave which consists of 748 observations from 137 centers. We use a balanced panel of 130 centers for which there is complete date for the analysis. The centers used in the analysis are from 38 different Dutch municipalities which are shown in figure 5.5.

Quality is measured using the Classroom Assessment Scoring System (CLASS), one of the scales introduced by developmental psychologists to measure the quality of child-caregiver interaction in classrooms. CLASS consists of two domains: instructional support and emotional support. Each domain is made up of several dimensions on which the observers grade the classroom interaction. The emotional support dimensions[4] are i) positive climate, ii) teacher sensitivity, iii) behavior guidance and iv) regard for child perspectives. Instructional support consists i) facilitation of learning and development, ii) quality of feedback and iii) language modeling. Each dimension is graded by the observer on a discrete scale from 1 to 7. Scores between 1-2 are considered to be low, 3-5 average and 6-7 high. The domains are constructed by simply taking the means of the dimensions. The overall quality score is the mean

[3]Future waves will track children into primary schools and will no longer measure child care centers' quality.

[4]An additional dimension named negative climate is collected but has low variation, is coded in reverse (1 being highest as opposed to 7) and its effect should be captured by the positive climate measure. Pakarinen et al. (2010) found a similarly low variation in Finland for the negative climate dimension and concluded that CLASS measures are a better predictor of classroom quality when negative climate is excluded. For the Pre-Cool survey, Leseman and Slot (2013) reports a low variation for the negative climate measure, since almost all classrooms score very low on it.

of the two domain scores. Development psychologists often use factor analysis to contract the quality scores but the means are easier to interpret in terms of economic significance. We used factor analysis to construct domain scores for which the same regressions were fitted as a robustness check. The factor loadings are reported in Appendix 5B and appear to be around 0.7 for all dimensions except the "regard for child perspectives" dimension.

Wave 1 observations were made in late 2010 and early 2011. Wave 2 was collected exclusively in 2012. Figure 5.9 in Appendix 5B presents the number of observations made in each month. A minority of observations were made in 2010 and limiting wave 1 observations to those collected in 2011 or wave 2 observations to those made before April 2012 hardly affects the results. 15 time fixed effects are included in most estimations, to control for the month and year in which the observation was made.

Table 5.2: Quality indicators of Dutch child care services before and after the subsidy reduction

	Wave 1		**Wave 2**	
	Daycare	**Playgroup**	**Daycare**	**Playgroup**
Process quality indicators				
Emotional support	5.011	5.054	4.446	4.636
	(0.855)	(0.865)	(0.736)	(0.699)
Instructional support	3.093	3.554	2.611	3.270
	(1.072)	(1.145)	(0.800)	(0.824)
Average quality	4.052	4.304	3.529	3.953
	(0.863)	(0.910)	(0.675)	(0.680)
Structural quality indicators				
Number of children	9.726	10.073	9.151	10.587
	(3.145)	(3.982)	(3.148)	(3.465)
Number of adults	1.968	2.214	1.955	2.291
	(0.733)	(0.858)	(0.812)	(0.927)
Observations	392	466	355	411
Number of centers	53	77	53	77

Table 5.2 presents the averages and standard deviations of the quality indicators for daycare centers and playgroups before and after the subsidy reduction. The average quality of Dutch child care centers is around the average level 4. The scores are higher for emotional support than instructional support. Pre-treatment scores for average quality are around 4 for playgroups as well. Post-treatment scores are lower for both but the drop in scores is more noticeable and significant for daycare centers,

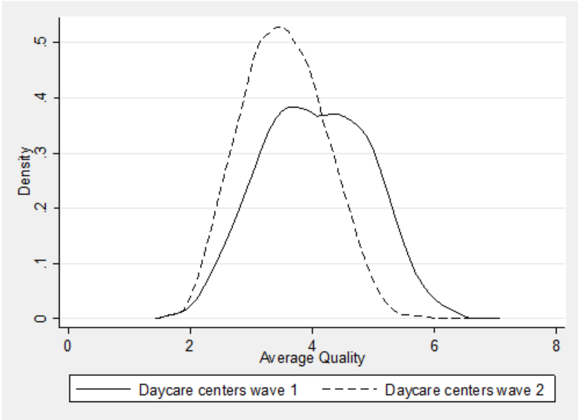


Figure 5.3: Distribution of child care quality in daycare centers

mostly due to the drop in instructional support. Difference in differences between the two periods of average quality in daycare centers and playgroups has a value of -0.172.

While Table 5.2 shows the means and standard deviations, Figure 5.3 and 5.4 presents the kernel distributions of the quality scores. Quality score distributions of playgroups and daycare centers are quite similar in wave 1. In wave 2 daycare centers' distributions shift noticeably to the left. Figures 5.4 also shows the distributional shift for the quality of playgroups; there are fewer playgroups with high quality scores in wave 2 compared to wave 1 and the right side of the distribution is almost truncated.

To analyze the effect the subsidy reductions had on quality, we use linear and non-linear estimators. The linear model estimates the mean impact of the subsidy reduction on daycare quality using the mean values of playgroups' quality as the control. We test the robustness of the linear results using the synthetic control method designed by Abadie et al. (2010). The synthetic control method allows us to put more weight to changes in quality of those playgroups that are more similar to daycare centers in terms of other observable characteristics such as area income or center age.

The linear DD models the distributional shift in daycare centers and playgroups in wave 2 that can be seen in figures 5.3 and 5.4. However, for both center types

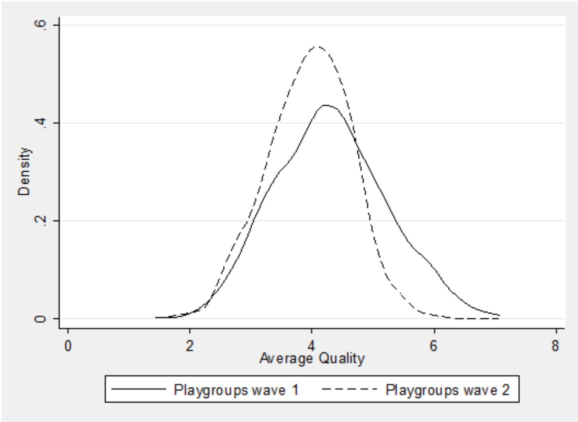


Figure 5.4: Distribution of child care quality in playgroups

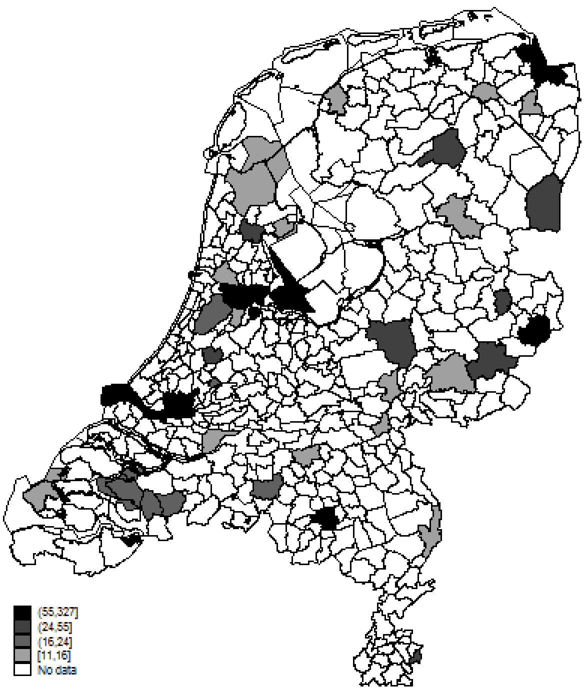


Figure 5.5: Number of class observations per municipality

the variation in quality drops. Furthermore, linear DD models assume additivity and homogenous effects on all daycare centers. To take the change in the distributions and potential heterogeneous effects for different quality levels into account, we make use of the changes-in-changes (CIC) model introduced by Athey and Imbens (2006) and the recentered influence function method of Firpo et al. (2009). The non-linear models take into account changes in the complete distribution of quality of both playgroups and daycare centers. In addition, they allow the calculation of the effects at different levels of quality, invariant to a monotonic transformation of quality.

There are a few potential concerns with DD analysis. The primary question of validity is whether the subsidy reduction is unrelated to a sudden decrease in child care quality. Since the reduction in 2012 was a part of a general austerity drive in the Netherlands and its potential costs and benefits were analyzed mostly from a labor supply perspective, the reduction in subsidies is most likely exogenous from centers' quality. A weakness of our particular data is that we cannot control for compositional effects with regards to parents' characteristics. For example, subsidy cuts may cause a switch between formal and informal care, which would affect quality.

5.5 Average Treatment Effects

5.5.1 Empirical methodology

As the first step in our analysis, we use linear DD models to estimate the effects of the subsidy reduction. The classroom observations belong to one of two categories given by the group variable $D_i \in \{0,1\}$ which is 0 for observations from playgroups and 1 for daycare observations. In the second wave when $T_t = 1, T_t \in \{0,1\}$, daycares are affected by the subsidy cut. Treatment is indicated by the variable $I_i = D_i * T_i$.

Using a difference-in-differences model, the average treatment effect can be estimated using OLS:

$$y_i = a + \beta_1 D_i + \beta_2 T_t + \rho I_i + b_t + c_j + e_i \tag{5.1}$$

In equation 5.1, the parameter of interest is ρ which is the treatment effect. We add two sets of additional controls, b_t are time fixed effects for the month of the observation and c_j are center fixed effects. Not all classrooms were observed in the same month in the first and second wave. Fixed effects are thus added for each month and year combination in which the quality observation was made. Center fixed effects are added since child care markets tend to be local and centers differ across other characteristics such as size. While the child-to-staff ratio in the Netherlands is regulated in both playgroups and daycare centers, the numbers could vary during the observations. We checked whether the numbers of children and adults in classrooms were affected by the subsidy cuts and there does seem to be a significant decline in both. We test the robustness of the estimates with and without these variables.

The second linear estimator used is the synthetic control method of Abadie et al. (2010). The synthetic control model explicitly takes into account the uncertainty about the validity of the control group and estimates the treatment effect ρ using equation 5.2. Since all daycare center observations are assumed to be affected by the same subsidy cut, quality observations from all daycare centers are first aggregated to construct an average daycare center where $i = 1$. Each of the n playgroups is then weighed using the vector $W = \|w_{i+1}, ..., w_{1+n}\|$ where $\|w_2 + ... + w_{i+n} = 1\|$ to generate a counterfactual control group that most closely resembles the daycare centers if a subsidy cut had not occurred.

$$\rho = Y_1 - \sum_{i=2}^{i+n} w^N Y^N \tag{5.2}$$

The weights are assigned using a set of covariates Z, which also includes quality before the subsidy cut to minimize the difference in observable characteristics between the average daycare center and the synthetic control of playgroup centers. More technically, the vector W minimizes $(Z^I - Z^N W)' V (Z^I - Z^N W)$, where matrix V indicates the relative importance of Z in predicting outcomes Y. Abadie et al. (2010) show that a synthetic control that minimizes the differences in Z and pre-intervention outcomes at least approximates differences in unobserved characteristics as well, and provides a more general estimator than the DD model, which is a specific case of the synthetic model where all weights are equal $(w_2 =, ..., = w_{i+n})$.

5.5.2 Results

The results for the estimations can be seen in table 5.3. The treatment effect is negative in all models. In the first model, we included only child care center type, the wave the observation is from and the treatment variable. The second model replaces the wave variable with year-month fixed effects to control for the timing of the observation. Treatment effect rises to -0.19 in this case. The third model adds municipality fixed effects in order to control for market heterogeneity, which further increases the treatment effect to -0.22. In the fourth model, municipality interactions with the center type are added to control for market heterogeneity differences between daycare centers and playgroups. The results show little difference compared to model (3). The final model adds center fixed effects and shows a similar treatment effect to models with municipality controls.

We report robust standard errors and standard errors clustered at different higher levels of aggregation. Specifically, we use standard errors clustered at the center-wave, center and municipality level. Bertrand et al. (2004) note that serial correlation in time series data can cause overrejection in DD estimates, but our data is only comprised of two waves. While the effects sizes do not vary between the models with and without center and municipality fixed effects by much, clustering seems to increase the size of the standard errors as expected. Model 5 likely provides the most reliable estimate since it takes into account center heterogeneity and includes year-month fixed effects. In that case, the coefficient is highly significant when robust standard errors or clustering is used per center in each wave. However, standard errors rise when they are clustered at the center or municipality level.

Table 5.3: Effects of the 2012 subsidy reduction on average quality

Model	(1)	(2)	(3)	(4)	(5)
Treatment effect	-0.1725	-0.1942	-0.2216	-0.2242	-0.2124
S.E. Robust	(0.0780)**	(0.0786)**	(0.0759)***	(0.0726)***	(0.0695)***
S.E. Clustered					
Center*wave	(0.1424)	(0.1402)	(0.1313)*	(0.1193)*	(0.0953)**
Center	(0.1285)	(0.1295)	(0.1333)*	(0.1311)*	(0.1335)
Municipality	(0.1551)	(0.1427)	(0.1513)	(0.1571)	(0.1612)
Time controls	Wave	Year-month	Year-month	Year-month	Year-month
Municipality FE	-	-	+	-	-
Center type*Munic. FE	-	-	-	+	-
Center FE	-	-	-	-	+
Observations	1,624	1,624	1,624	1,624	1,624
Number of centers	130	130	130	130	130

Standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1 There are 260 clusters at the time x center, 130 clusters at the center and 38 clusters at the municipality levels.

The results in Table 5.3 show a generally negative effect from the subsidy reduction on daycare centers' quality. When DD models are fitted for all seven dimensions and instructional and emotional domains' factor scores separately, the coefficients are negative for both domains, and all individual dimensions as shown in table 5.11

in Appendix 5B. The effect sizes are larger and more significant for the instructional support domain. The larger effect on instructional support seems to be driven by facilitation of learning and development dimension. Previous literature has shown that instructional support measures are particularly important for school readiness (Mashburn et al., 2008). Especially in the Netherlands, quality scores were already below average for instructional support. Further decreases are more likely to have negative consequences on long term outcomes.

The effect on mean quality of 0.2 is around a third of the standard deviation of average quality. For the US, Duncan (2003) finds that a reduction of one standard deviation in process quality is associated with a decrease of a tenth of a standard deviation of cognitive scores for small children. If the association between child care quality and child development in the US is similar to the Netherlands, the subsidy reduction would have decreased cognitive development of Dutch children attending daycares by 3% of a standard deviation. The negative effects we find might be transitory since we are only looking at the year immediately after the subsidy reduction. In the case of child care however, short or long-term effects may be equally significant. Low quality care for even a few years may have long lasting effects on children currently in child care, since the formal child care period is only until the age of 4 in the Netherlands.

While the results suggest that process quality declined as a result of the subsidy cuts, there also appear to be effects on more structural factors such as the number of children and adults in each classroom. Table 5.11 in Appendix 5B shows that the number of children and adults in each classroom declined. This might be a result of the decline in demand for which the centers have not yet adjusted the number of groups. Since group size has a negative impact on process quality, including these variables in the main regression slightly increases the coefficient which remains below 0.25. Finally, we checked whether the activity assessed by the Pre-Cool observer varied significantly by using the most common activity, free play, as a dependent variable. In that case, there do not appear to be any significant effects.

As an informal check on whether there was significant sample selection, Table 5.8 in Appendix 5B separately shows the wave 1 quality values of centers that are not in wave 2. There is no evidence of sample selection for daycare centers where the average wave 1 quality is almost the same as the observed sample. Among playgroups, centers that are not in wave 2 have lower average quality. Simply including these centers in the regressions results in slightly larger treatment effects.

A potential issue with the DD estimates is that not all playgroups may be good controls for daycare centers. Playgroups and daycare centers may be located in regions with systematic differences in terms of income and child care markets. To test the robustness of the DD estimates, we implement the synthetic control model introduced by Abadie et al. (2010) as an alternative estimator. As covariates in constructing the weighing vector w that is used to calculate the synthetic control group, we introduce new variables at area and center levels. Both of the fitted models presented in Table 5.4 use the first wave values of child care quality to construct the synthetic control estimates. To control for area level differences, we use municipality level information on income from 2009 and the density of child care centers for years the observations are from. The results using the area level controls are presented on the left side of Table 5.4. We also have data on center characteristics from a managerial survey that was done as a part of the Pre-Cool study. On the right hand side, we also include center level controls on center age, the size of the parent firm as measured by the number of the other centers owned and the average number of opening hours. The center age and firm size variables are both linear in categories[5]. The managers' surveys these variables are based on are incomplete, which results in a loss of observations. According to table 5.4, the estimated effects are on average -0.30, which is larger than the full sample results from the linear DD model with center fixed effects in Table 5.3.

Table 5.4: Synthetic control estimates of the 2012 subsidy reduction effects on average quality

	Area controls			Area and center controls		
	Wave 1	Wave 2	Diff	Wave 1	Wave 2	Diff
Daycare centers	4.0638	3.5140	0.5498	4.0183	3.5392	0.4791
Synthetic control	4.0762	3.8674	0.2088	4.0054	3.7788	0.2266
Treatment effect		-0.3410			-0.2525	
Number of playgroups		77			39	

[5]Center age categories: <1 year, 1-2 years, 3-4 years, 5-10 years, >10 years. Firm size categories (# of centers): 1, 2-5, 6-10, >10.

5.6 Estimating quantile effects

5.6.1 Empirical methodology

Next, we estimate models that takes into account the shift in the full distribution of quality values. First, we implement the changes-in-changes (CIC) model of Athey and Imbens (2006) and then confirm the results using the recentered influence function method of Firpo et al. (2009). The non-linear models relax the additivity assumption in the DD model and compare the changes in distributions rather than the means. To compare the results, we also fitted the quantile difference-in-differences (QDID) model. The quantile models have two potential advantages over the linear DD model in our case. First is the shift in the distributions of both playgroups and daycare centers' quality values from wave 1 to wave 2. Second, daycare centers with different starting levels of quality in wave 1 might react differently to the subsidy cut.

The CIC model, changes in the variance of outcomes over time within treatment and control groups are explained through changes in the production function for the outcome defined by $Y = h^I(u,t)$ where u are unobserved characteristics at time t. The restriction of the function $h(.)$ is that it is monotonic and increasing in u. In contrast to the DD model which ignores changes in the distribution of outcomes and provides identification through the change in conditional means, identification in the CIC model is based on the full distribution of control and treatment groups before and after the treatment. Given an outcome value in the treatment group in the first wave Y_{10} and its associated quantile q, we first find the matching value in the first wave control group $Y_{00} = Y_{10}$ with its associated quantile q'. Taking into account the change in the cumulative distribution function of the control group in the second wave, we can find the second wave value Y_{01} at quantile q'. The difference between the first and second wave values of the control group at quantile q' ,s used by the counterfactual change for quantile q of the treatment group. Athey and Imbens (2006) show that the complete counterfactual distribution of the treatment group F_{Y^N} can be obtained using equation 5.3. Once the complete counterfactual distribution is constructed, the average treatment effect can be calculated by taking the difference between the realized distribution of the treatment group and the counterfactual distribution.

$$F_{Y_N}(y) = F_{Y_{10}}(F^{-1}_{Y_{00}}(F_{Y_{01}}(y))) \tag{5.3}$$

Finally, we apply the recentered influence function method of Firpo et al. (2009), we follow the application of Havnes and Mogstad (2011b) of the threshold DD (TDID) model. Firpo et al. (2009)'s shows that the unconditional quantile regression can be redefined as a linear regression where the dependent variable is the probability that an observed outcome is greater than a given level. By estimating equation 5.4 using OLS, we can then determine the effect of the subsidy reduction I_i on the possibility thatthe observed quality Y_{it} is greater than the quality level at y.

$$Pr(Y_{it} > y) = a^y + \beta_1^y D_i + \beta_2^y T_t + \rho^y I_i + b_t^y + c_j^y + e_i \tag{5.4}$$

5.6.2 Results

Using the CIC and threshold DD methods, the full counterfactual distribution has to be estimated and it is possible to calculate the effects at different quantiles. Since the standard errors cannot be clustered in CIC and threshold DD models, the standard errors for these models will be underestimated. The analytical standard errors that Athey and Imbens (2006) provide do not differ significantly from bootstrapped standard errors. Similarly, the robust standard errors used for the TDID model are similar in size to the bootstrapped standard errors. Due to the finite sample size, bootstrapped and analytical standard errors are about identical.

Table 5.5 shows the average treatment effect along with the estimated effects at 10th, 25th, 50th, 75th and 90th quantiles. We also plot the quantile effects using 0.1 intervals. The average treatment effect is similar in size to the estimates from the linear DD models in both the CIC and TDID models. The coefficients for the different quantiles show that the effects are larger in the middle of the quality distribution, especially in the TDID and QDID models. The linear quantile (QDID) model suggests that the effects are strong also at the bottom of the quality distribution, but given the large change in distributions from wave 1 to wave 2, the results from the non-linear models may be more informative.

A possible explanation for the heterogenous effects may be that the low quality child care centers simply do not have any more room to cut costs and lower quality given the current regulations. At the same time, highest quality centers may also be catering to parents with strong tastes for child care quality or very high income and thus low demand elasticity. A more straightforward explanation is that the subsidy cuts were not homogenous for all income groups. If higher income parents also use higher quality care, the heterogeneous effects would reflect the larger cuts for middle

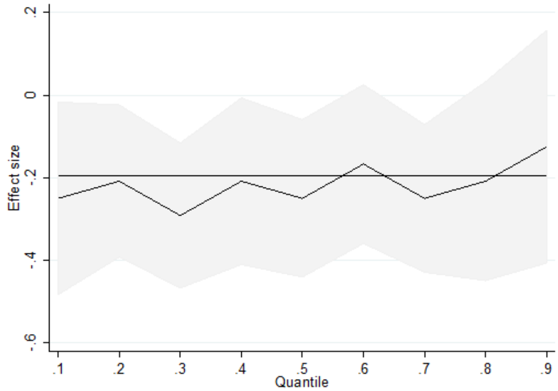


Figure 5.6: Quantile Effects - QDID

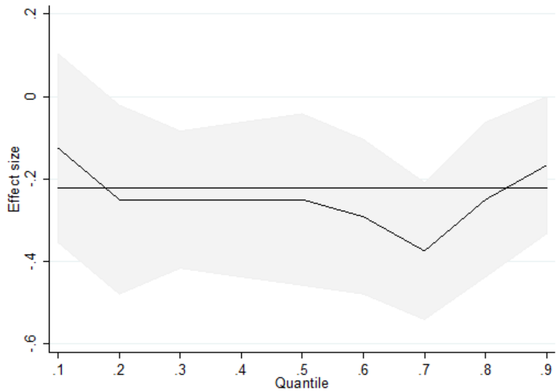


Figure 5.7: Quantile Effects - CIC

and higher income families.

We cannot use clustered standard errors for quantile effects. To allow for common effects at the center level, we average classroom quality per center and fit the CIC and threshold DD models at the center level instead of the classroom level. The results are presented in table 5.12 in Appendix 5B. The average treatment effects are larger when center averages are used but the significance levels are at the 5% and 10% levels rather than 1% due to the larger standard errors. The quantile effects remain

Table 5.5: Effects by quality quantiles

	Avg. effect	**Quantile**				
		0.10	0.25	0.50	0.75	0.90
QDID | No controls						
Effect size		-0.25	-0.2083	-0.25	-0.3333	-0.125
S.E. Robust		(0.1192)**	(0.0944)**	(0.0973)**	(0.1022)***	(0.1440)
CIC						
Effect size	-0.2217	-0.125	-0.2917	-0.25	-0.3333	-0.1667
S.E. Bootstrap	(0.066)***	(0.1063)	(0.1169)**	(0.1065)**	(0.0957)***	(0.0850)**
TDID | No controls						
Effect size	-0.1942	-0.2197	-0.4488	-0.3314	-0.2187	0.077
S.E. Robust	(0.0800)**	(0.1352)	(0.1103)***	(0.1115)***	(0.1118)*	(0.1408)
TDID | With controls						
Effect size	-0.2124	-0.1786	-0.4715	-0.3522	-0.2211	0.0471
S.E. Robust	(0.0712)***	(0.1307)	(0.1031)***	(0.1035)***	(0.1076)**	(0.1365)

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parenthesis. We use 200 repetitions for the bootstrapped standard errors. *** p<0.01, ** p<0.05, * p<0.1. All models (except the CIC model) include year-month fixed effects. QDID and TDID models with controls also include center fixed effects for 129 centers.

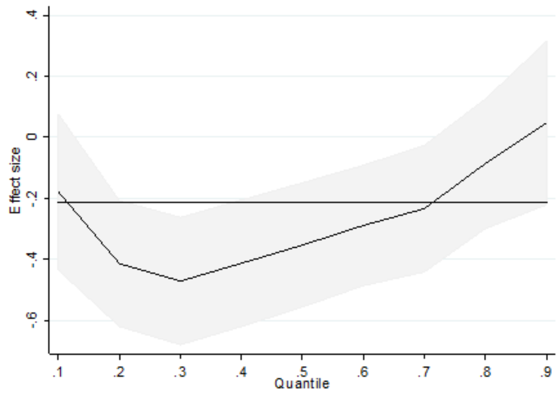


Figure 5.8: Quantile Effects - TDID

significant at the 0.25 and 0.5 quantiles but turn insignificant at the 0.75 quantile for the threshold DD model using center averages..

5.7 Conclusions

We examine the impact of child care cut reduction on child care quality in the Netherlands using a natural experiment with playgroups as the control group. The results show that process quality in Dutch daycare centers declined as a result of the subsidy cut. The baseline treatment effects estimated using linear DD models are robust across linear DD models, synthetic controls, threshold DD and CIC models. Estimates by quantiles of quality show that the effects are concentrated in the middle of the quality distribution.

Currently there appear to be two policy objectives pulling in opposite directions when it comes to child care subsidies and child care services in general. On the one hand, research showing significant positive gains in future outcomes of children attending high quality care has led to discussions on extending the coverage of child care services. On the other hand, austerity measures in many European countries is leading to cuts in child care spending. These cuts are assumed to have low costs since the labor supply effects are generally found to be limited. However, cost on child care quality from cuts are typically ignored, since there is a lack of empirical evidence in this area.

An interesting question to consider is how increases in subsidies would influence child care quality. A straightforward interpretation of the Dutch experience would be that an increase in subsidies would raise both quality and coverage. However, there is no evidence to suggest that the effects of child care subsidies are symmetric. Higher demand as a result of child care subsidies can lead to higher prices if supply does not adjust accordingly and parents' choices are limited. The effects of subsidy increases would need to be considered within the specific market in which they are implemented. Easy entry into the market to allow for more parental choice and regulations on prices may be required to realize concurrent increases in child care centers' coverage and quality. Alternatively, more direct options to increase quality such as structural regulations or changes in the pedagogic curriculum can be explored.

5.8 Appendix 5A

In this Appendix, we calculate the net income and net child care costs of various household types to see what the net increase in monthly child care costs are. To calculate net family incomes, the MICROTAX programme of the Dutch Central Planning Bureau (CPB) is used. We assume in all cases that the total monthly hours of child care used is 120. In table 1, net costs are calculated for a single parent family, a couple with one parent working full time and the other part-time and a dual income family. In table 2, same calculations are presented for families with two childen in formal child care.

Table 5.6: Child care costs of median income households with one child

	Single parent		**1.5 income**		**Dual income**	
Family income	33150		49725		66300	
Net family income	24467		38006		47877	
	2011	*2012*	*2011*	*2012*	*2011*	*2012*
Gross child care cost	758.4	774	758.4	774	758.4	774
Net cost	125.89	151.99	193.43	225.26	295.78	336.69
% change	20.73%		14.68%		13.83%	

Table 5.7: Child care costs of median income households with two children

	Single parent		**1.5 earners**		**Dual earners**	
Family income	33150		49725		66300	
Net family income	24467		38006		47877	
	2011	*2012*	*2011*	*2012*	*2011*	*2012*
Child care cost (x2)	758.4	774	758.4	774	758.4	774
Net cost	163.81	229.19	444.42	551.38	646.92	798.65
% change	39.91%		24.07%		23.46%	

5.9 Appendix 5B

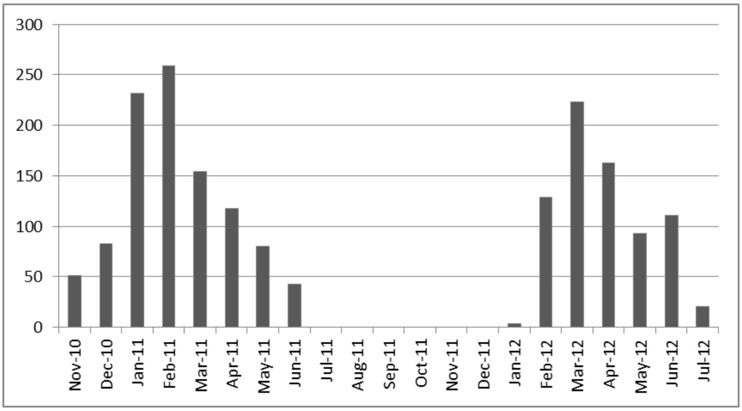


Figure 5.9: # of classroom observations each month

Table 5.8: Wave 1 summary statistics of centers missing in wave 2

	In Both Waves		First Wave Only	
	Daycare	**Playgroup**	**Daycare**	**Playgroup**
Emotional support	5.011	5.054	5.048	4.874
	(0.855)	(0.865)	(0.682)	(0.919)
Instructional support	3.093	3.554	2.985	3.04
	(1.072)	(1.145)	(0.904)	(0.935)
Average quality	4.052	4.304	4.017	3.957
	(0.863)	(0.910)	(0.657)	(0.830)
# of children	9.726	10.073	8.585	9.549
	(3.145)	(3.982)	(2.445)	(3.460)
# of adults	1.968	2.214	1.858	2.071
	(0.733)	(0.858)	(0.795)	(0.857)
Observations	392	466	88	92
# of centers	53	77	11	16

Table 5.9: Summary statistics of center averages

	Wave 1		Wave 2	
	Daycare	**Playgroup**	**Daycare**	**Playgroup**
Emotional support	5.010	5.043	4.434	4.627
	(0.659)	(0.662)	(0.469)	(0.505)
Instructional support	3.117	3.543	2.594	3.248
	(0.766)	(0.855)	(0.525)	(0.580)
Average quality	4.064	4.293	3.514	3.937
	(0.668)	(0.713)	(0.440)	(0.488)
Number of children	9.644	10.149	9.122	10.464
	(1.899)	(2.804)	(1.941)	(2.443)
Number of adults	1.960	2.181	1.988	2.309
	(0.532)	(0.594)	(0.599)	(0.815)
Number of centers	53	77	53	77

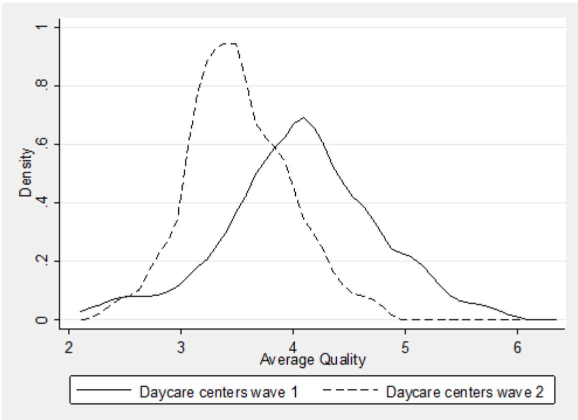


Figure 5.10: Distribution of child care quality in daycare centers' (averages)

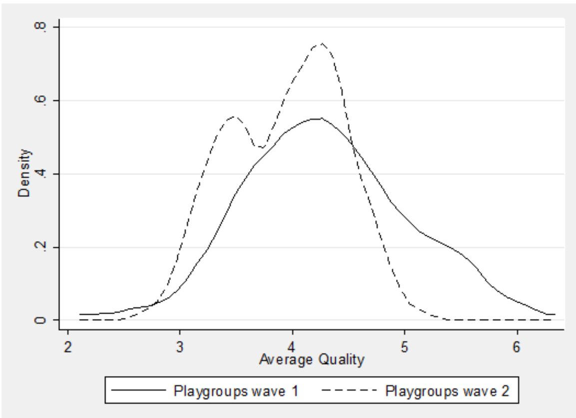


Figure 5.11: Distribution of child care quality in playgroups' (averages)

Table 5.10: Factor loadings for quality domains

	Factor Loadings
Emotional Support	
Positive climate	0.7103
Teacher sensitivity	0.7709
Regard for child perspectives	0.3383
Behavior guidance	0.6694
Instructional Support	
Facilitation of learning and development	0.7664
Quality of feedback	0.749
Language development	0.7313

Table 5.11: Effects on individual quality indicators

	Base	**Center Fixed Effects**
Structural indicators		
Number of children	-1.0777***	-0.9734***
	(0.3554)	(0.3529)
Number of adults	-0.1143	-0.1247*
	(0.0855)	(0.0754)
Free play	-0.0177	-0.0119
	(0.0443)	(0.0463)
Emotional support indicators		
Positive climate	-0.0740	-0.0549
	(0.1097)	(0.0984)
Teacher sensitivity	-0.1767*	-0.1244
	(0.1026)	(0.0989)
Regard for child perspectives	-0.2184*	-0.2569**
	(0.1270)	(0.1243)
Behavior guidance	-0.2550**	-0.2609**
	(0.1070)	(0.1025)
Instructional support indicators		
Facilitation of learning and development	-0.4066***	-0.4509***
	(0.1209)	(0.1164)
Quality of feedback	-0.2115*	-0.2348**
	(0.1078)	(0.0986)
Language development	-0.0041	-0.0660
	(0.1137)	(0.1020)
Factor variables		
Emotional support	-0.1656**	-0.1445*
	(0.0832)	(0.0758)
Instructional support	-0.1779**	-0.2136***
	(0.0811)	(0.0733)

Robust standard errors are used in both regressions.
*** p<0.01, ** p<0.05, * p<0.1

Table 5.12: QREG, CIC and TDID estimates using center averages

		Quantile				
	Avg. effect	0.1	0.25	0.5	0.75	0.9
QREG						
Effect size		-0.0608	-0.0521	-0.3125	-0.5885***	-0.1644
S.E.		(0.3552)	(0.1597)	(0.2108)	(0.1770)	(0.2010)
TDID | FE						
Effect size	-0.2441*	-0.0170	-0.4219**	-0.6501***	-0.239	-0.0806
S.E.	(0.1332)	(0.1525)	(0.1881)	(0.2070)	(0.1757)	(0.2942)
CIC						
Effect size	-0.3215**	-0.0833	-0.3750	-0.6250**	-0.5000**	-0.2500
S.E. Bootstrap	(0.1759)	(0.3933)	(0.3401)	(0.3082)	(0.1913)	(0.2338)

Standard errors in parenthesis. 200 repetitions are used for the bootstrapped standard error errors. ***p<0.01, ** p<0.05, * p<0.1. The QREG model includes 14 year-month fixed effects. The TDID model includes 129 centers fixed-effects and 14 year-month fixed effects. The date of the first class observation in each wave is used to construct year-month fixed-effects.

Chapter 6

Child Care Quality and the Labor Supply of Married Women

6.1 Introduction

Increasing female employment has been a major policy goal for some time. The main instrument in stimulating female labor supply has been child care subsidies designed to increase access and affordability of child care for mothers of young children. Recent elasticity estimates form the Netherlands, Sweden and Norway show insignificant or small effects from further decreases in child care prices (Wetzels, 2005; Lundin et al., 2008; Kornstad and Thoresen, 2007). Literature is silent on how child care quality, which has become a policy goal in itself, affects female labor supply.

Especially in Western Europe, high labor force participation rates combined with low child care prices have begun to limit the effectiveness of further subsidies to raise labor supply. Recent elasticity estimates from the Netherlands, Sweden and Norway show insignificant or small effects from further decreases in child care prices (Wetzels, 2005; Lundin et al., 2008; Kornstad and Thoresen, 2007). Limited increases from lower child care prices do not imply, however, that female labor supply has reached a ceiling or has equalled that of men. Female participation figures are closer to men's in Western Europe, but women work fewer hours. Apparently, even with very low prices mothers are unwilling to use child care and increase working hours further, which may be related to concerns over the quality of care children receive.

In this chapter, we estimate the effect of child care quality on the labor supply of married women. The focus is on the Netherlands where part-time work is common among women (Freeman, 1998), we study the choice between non-participation, part-time employment and full-time employment.

To analyze the role of child care quality in labor supply, we utilize a mixed multinomial logit model that accounts for unobserved heterogeneity. The primary dataset is Pre-Cool, a panel survey for the period 2010-2012 on child care quality in the Netherlands that also includes information on parents' background characteristics and employment. The estimation relies on the surprisingly large variation across child care centers' quality, which is mostly explained by the location of the market that they are placed in. The Pre-Cool data is supplemented with administrative data from 2009 wave of the Labor Market Panel of Dutch Statistics which is used to predict the wages of the Pre-Cool sample.

Our main findings are the following. First, we find no link between child care quality and married women's labor supply. In line with the previous literature, center prices have a negative effect on labor supply. We also find a fairly large wage elasticity for Dutch women with young children.

The mixed logit model has previously been used to estimate the effect of child care prices on labor supply. The present chapter adds child care quality to the existing structural labor supply models (Powell, 2002; Tekin, 2007; Kornstad and Thoresen, 2007). While the importance of quality is raised in relation to its effect on child development in empirical work, the link between labor supply and quality is only noted in theory without an empirical application (Blau and Currie, 2006). Quality is typically treated as a latent and constant variable, since observations of child care quality is scarce (Ribar, 1995). Despite the theoretically proposed positive link between child care quality and female labor supply, our results seem to suggest that parents are unable to take child care quality into account in their employment and child care choices.

In the next section, we describe the mixed logit model we use to analyze the impact of child care quality and prices on female labor supply. The third section introduces the two datasets used to estimate the model. Section 4 provides the estimation results and simulated elasticities. Section 5 concludes.

6.2 Theory and Methodology

We use a discrete choice model to analyze mothers' decisions with regard to employment and child care type. For tractability, we assume the mother's decision to work occurs after her partner's income is known (Killingsworth and Heckman, 1986). Having a higher income partner is thus one of the variables in a vector of observable personal characteristics X. Given X and u_1, a mother's utility within category k is a function of her leisure time L, the quality of her child Q, consumption C and unpaid hours of child care H_{p_u}. The category k is defined by the categorical, discrete variable $K = 1...k$, where each category denotes a different employment status. Categories may have other unobserved characteristics which can influence utility. For example, choosing a state with full-time work might be stigmatizing for some women regardless of the quality of child care. The unobservable characteristics are given by u_1. The resulting utility function is given by:

$$U = U(L, Q, C, K; X, u_1) \tag{6.1}$$

The budget constraint of the household depends on the wage w which varies between full-time w_f and part-time employment w_p, the price of child care that is p_c per hour of center care H_{p_c} and p_i per hour of informal care H_{p_i} and other income N. Each woman can fall within one of the five categories given in Table 6.1. We only distinguish between employed women for child care use, even though there are some women who also use formal child care despite having reported non-participation.

The budget constraint for the maximization problem depends on the category chosen. Each constraint depends on the wage w which varies between full-time w_f and part-time employment w_p, price of child care that is p_c per hour of center care H_{p_c} and p_i per hour of informal care H_{p_i} and income from sources other than wages N. We constructed the five alternative categories presented in table 6.1, each for a different level of employment and child care type.

Child quality is a function of the hours of paid and unpaid child care, the hours the mother spends with the child during her leisure L, and the paid child care quality A. A contentious issue is how to include child care quality. Previous studies have treated child care quality as a variable maximized by the mother in the utility function, allowing for its treatment as a latent variable that does not appear in the indirect utility function. We do not assume that child care quality is maximized by the mother the way employment and leisure hours are. Instead, mothers are assumed to use the child care with a given quality A that is available to them. This does not mean that two mothers living in the same area will have the exact quality child care. Some parents will be able to choose better quality child care because they can distinguish between high and low quality child care. However, the preference for high quality over low quality is universal for all parents the same way higher wages are always preferred over lower wages. We take into account personal characteristics X such as education that might affect the ability of the parents to distinguish between high and low quality child care when we estimate the quality values.

$$Q = Q(H_{p_i}, H_{p_f}, L; X, A) \tag{6.2}$$

A time constraint is needed to close the model. Since we do not utilize time-use data, we cannot distinguish between time that the mother actually spends with the child and her leisure. Following the previous literature, the basic time constraint is given by equation (6.3) where the hours work E equals the hours of unpaid and paid child care (Ribar, 1995; Tekin, 2007).

$$L = 1 - E = 1 - (H_{p_f} + H_{p_i}) \tag{6.3}$$

The outcome of interest in the empirical model is not utility itself, which is unobserved. Instead, we are interested in estimating the probability of choosing category k. Assuming that the mother maximizes her utility subject to (6.3), she chooses a specific value for L, H_{p_i}, H_{p_f} and C in each category. To estimate the model, we specify a linear approximation for the indirect utility function in category k for individual i given by:

Table 6.1: Category Definitions and Budget Constraints

	Employment	**Center Child care**	**Budget Constraint**
1	No	No	$C = N$
2	Part-time	No	$C = N + w_p - p_i H_{p_i}$
3	Part-time	Yes	$C = N + w_p - p_f H_{p_c}$
4	Full-time	No	$C = N + w_f - p_i H_{p_i}$
5	Full-time	Yes	$C = N + w_f - p_f H_{p_c}$

$$V_{ik} = X_i\beta + a_1 p_{ik} + a_2 w_{ik} + a_3 A_{ik} + e_{ik} \tag{6.4}$$

Equation (6.4) defines the indirect utility function that can be estimated given X_i, p_{ik}, w_{ik} and A_{ik}. Adding an unobserved random component e_{ik} results in an additive random-utility model that can be estimated using a multinomial logit model (Cameron and Trivedi, 2009). The category k is observed if k has the highest utility of the alternatives. In line with Blau and Hagy (1998), equation (6.5) states the model formally by defining the probability that outcome k is observed as the probability that category k results in a higher level of utility than all other alternatives.

$$Pr(k) = Pr(U_k > U_j) = Pr(e_k - e_j > a_1(p_j - p_k) + a_2(w_j - w_k) + a_3(A_j - A_k) \tag{6.5}$$

So far, we have not made any assumptions about the structure of the error term e_{ik}. The basic multinomial logit model assumes independence of irrelevant alternatives and that the error term is independently and identically distributed extreme value type 1. In line with the mixed logit model introduced in Revelt and Train (1998) we can add random components to the coefficients to capture heterogeneity in tastes. While we could allow all coefficients to vary randomly, this is generally not feasible in applied work due to computational constraints. Previous labor supply models using a similar random coefficient specification generally allow for the coefficient on income or leisure to have a random component (Van Soest, 1995; Haan, 2006). We allow for two variables' coefficients to have random components: quality and wages. Quality, wage and price variables are in the vector a of the variables that are alternative specific. The coefficients of quality and wage variables then take the form $a_i = a + \vartheta_i$ where a_i has a multivariate normal distribution with mean a, which allows the estimation of the distribution and covariance matrix of a_i. Since parents who are particularly concerned with quality may have more or less taste for income, the random components are allowed to be correlated. The alternative invariant individual characteristics X have fixed coefficients. The resulting mixed logit estimation for the probability of observing choice k given observed characteristics X_it and alternative specific characteristics S_{itk} can be written as:

$$P(k|X_{it}, a_{it}) = \frac{exp(X_{it}\beta_k + a_i S_{itk})}{\sum_{j=1}^{k} exp(X_{it}\beta_j + a_i S_{itj})} \tag{6.6}$$

In order to identify the model, the base category (non-participation) coefficients are all set to 0. To capture category effects, we introduce a fixed effect for each category. We expect that there are fixed costs associated with each category, whether it is unpaid care or travel to work and category specific fixed effects are meant to capture those.

The difficulty in estimating the model lies in assigning values to the random components. The likelihood function for individual i observed in category k shown by equation (6.6) can be expressed as an integral over the entire distribution of the unobserved heterogeneity terms as shown in equation (6.7). To estimate the likelihood function, recent literature has generally followed Train (2009) in using simulated maximum likelihood based on Halton sequences. The premise of the simulated maximum likelihood estimation is to make a large number of quasi-random draws of ϑ_i to determine the distribution that maximizes the likelihood function given in equation (6.7). [1]

$$P(k|X_{itk}, a_i) = \prod_{i=1}^{N} \int_{-\infty}^{\infty} \prod_{t=1}^{T} \prod_{j=1}^{k} \frac{exp(X_{it}\beta_k + a_i S_{itk})}{\sum_{j=1}^{k} exp(X_{it}\beta_j + a_i S_{itj})} f(a_i)d(a_i) \tag{6.7}$$

In order to estimate (6.6), we need values for wage, child care price and quality. These three variables are estimated using a reduced-form approximation of the demand functions. For identification of wages, quality and prices, we use the province that the parents are residing in as the exclusion restrictions (Tekin, 2007). Previous labor supply models have also used education variables to identify effects, but education is likely to have a positive effect on taste for employment which would imply that the elasticities for income become inflated when they are omitted from the main model (Keane, 2011). The underlying assumption for using province as the exclusion restriction is that the region that parents reside in does not affect the indirect utility function except through the available quality, price and wage levels. Labor markets and child care markets where wages, prices and quality are determined are expected to be geographically constrained, leading to significant variation

[1] the model is estimated using the STATA code made available by Hole (2007).

across Dutch provinces. Two wage equations are estimated, one for full-time and the other for part-time, since differences have been found in the wages of part-time and full-time workers in the Netherlands (Russo and Hassink, 2005). The basic form of the estimated equations for wages is given by equation (6.8), where D is a vector of dummies for the Dutch provinces and v_f is the error term. The form of the part-time wage equation is essentially the same as the full-time wage equation. Sample selection is corrected for using Heckman correction. Both part-time and full-time wage equations use the same first stage selection correction with the full sample of women to correct for employment. However, the second stages are split into to sub-samples of part-time and full-time working women.

$$w = X\beta_i + D\gamma_i + v_f \tag{6.8}$$

The Pre-Cool data does not have price or quality information for a large part of the sample because the center information is not collected for a part of the sample and because some parents do not use daycare centers. For the estimation of the price and quality equations, we thus use a Heckman selection model as well. The estimation structure for the binary variable y^*_{it} which is 1 when price and quality is observed, and the observed value y_{it} is given as a two equation model of the form shown in equations (6.9) and (6.10). To improve the identification of the selection parameters in the price and quality equations, we use the number of siblings as an exclusion restriction in the first equation. The assumption is that the number of siblings will affect the use of child care but not the price or quality. [2] In addition, price and quality observations are not available for four provinces (Groningen, Friesland, Utrecht [3], Limburg) and observations from these provinces are removed from the sample to estimate the model. Quality observations are available from Friesland in wave 1, but not in wave 2 while the other three provinces have no quality and price information in either wave. For consistency, we also estimate the wage equations without observations from these provinces.

$$y^*_{it} = X\beta_{it} + D\gamma_i + \varepsilon_1 \tag{6.9}$$

[2] Not using an exclusion variable and excluding siblings from the model gave similar results.

[3] There was one household from Utrecht that reported using an observed center but the center itself is in Almere and all other parents using it are from Flevoland. This observation is thus excluded from the analysis

$$y_{it} = X\beta_{it} + D\gamma_i + \varepsilon_1 \tag{6.10}$$

6.3 Data Description

The main data source we use is the Pre-Cool survey from the Netherlands. The Pre-Cool survey is a panel, regionally representative survey of Dutch children, parents and child care centers. The survey is made up of two samples. The first sample comes from the child care centers that are observed. In addition to parental questionnaires in filled by the parents, this sample includes information on the quality of child care at the center, although not all the selected centers had quality observations. The second sample, provided by Statistics Netherlands, serves as a control group and consists of other children from the areas that the centers are located in. No quality or price information is available for these children and the data is limited to parental questionnaires. The sampling strategy ensures that the final sample consists of children spread across the Netherlands both in and out of formal child care. The Pre-Cool panel was started when children were 2 years old and we use the first two waves. The first wave was collected at the end of 2010/beginning of 2011 and the second at the end of 2011/beginning of 2012. There are some observations in wave 2 that do not report the date the survey was filled and we treat those as having filled the survey in 2012. There are in total 659 households with two adults which filled out the parental questionnaires in both waves and for whom we have all background variables used in the estimation. While selective non-response from wave 1 to wave 2 is an issue, all parents had their child tested for the child development component of the study in both waves, indicating some level of cooperation with the study as a whole.

For the main model, we limit our sample to women in the survey with a partner who reports employment to avoid families where men might be the primary caregivers. The Pre-Cool survey includes a large number of personal characteristics for the parents such as education, hours worked, age and the number of other children. The hours worked question differs between wave 1 and wave 2. Wave 2 asks for the number of part-days worked while the wave 1 question has a number of options with different number of working hours. We code all women in the Pre-Cool sample who indicate working 32 or more hours (or more than 8 part-days in wave 2) as working full-time. Many of the fixed characteristics such as education and ethnicity only appear in the first wave while age (within categories) is only included in the second wave. Any household that has indicated hours of daycare use or has a child in one of the daycare centers of the Pre-COOL survey (with quality observations) is coded as using center based child care and all others are coded as not using child care including cases where the hours question is missing. The siblings variable that is available in both waves needs some interpolation since it is based on a question that asks the number of other children and non-response is high. We assume that non-response in this case implies 0 and to correct for potential measurement error, we use the response in the other wave if there was a response that wave. If the siblings variable is omitted from the analysis, both in the prediction equations and the main model, the effects are not significantly different.

Questions in the Pre-Cool survey regarding monthly income of each partner are only available in broad bands of 500 euros. We make use of the survey income variable for men as a control variable in the main model by taking the maximum in the two waves and constructing male income categories. There are around 20 households where male income is only indicated in one wave, and the available wave information is used in these cases. For a more exact measurement, hourly wages for women are estimated using the 2009 wave of an administrative household panel, the Labour Market Panel of Statistics Netherlands.The dataset is based on the Dutch Labor Force Survey which has been matched with the Social Statistical Panel that contains information on hours worked and wages and municipal administration data. Hourly wage equations as shown in equation (6.8) are estimated for both part-time and full-time working women with a partner whose youngest child is at most 4 years old. The resulting sub-samples consist of about 10000 women for the part-time estimation and 1200 for the full-time. The larger part-time female sample reflects the large proportion of Dutch women in part-time employment. The results in the wage estimates are in line with previous studies, with older and more educated women earning more. Additionally, F-tests on the province dummies shows that location is highly significant for both part-time and full-time wages. The estimated wage equations are used to impute the potential hourly log wages for part-time and full-time work of the women in the Pre-Cool sample. The summary statistics for the resulting background variables and predicted hourly wages man be seen in Table 6.2. The distributions of female hourly wages are presented in Appendix 6A along with the reduced form estimates for wages.

Gross wages estimated through reduced form equations were adjusted to annual wages and the net yearly earnings were calculated for each household under three

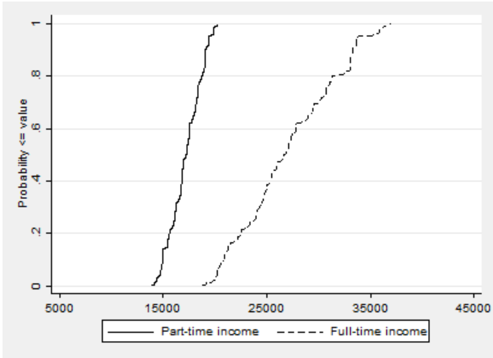


Figure 6.1: Predicted Female Income Distributions According to Employment

scenarios. Net earnings are calculated using the Microtax program of the Netherlands Bureau for Economic Policy Analysis (CPB) for the years 2010, 2011 and 2012. Under the first scenario, only the men are assumed to work and female earnings are zero. The second scenario calculates the earnings of women if they had been working part-time which is defined as 25 hours a week. The final scenario assumes that women in the households work full-time defined as 40 hours a week. Depending on which year the Pre-Cool survey was filled in, the imputed household earnings are adjusted using the Consumer Price Index (CPI) of Eurostat. Figure 6.1 presents the cumulative distributions of predicted family incomes for the three categories of female employment. The means presented in table 6.3 show that net income does not increase as much as expected from part-time to full-time work due to progressive taxation. In the main model, we use hourly net wages for women by dividing the predicted female net income by yearly working hours (1300 for part-time and 2080 for full-time).

Table 6.2: Sample Characteristics and Hourly Wages

Observed choice:	**No employment**	**Part-time No center care**	**Part-time Center care**	**Full-time No center care**	**Full-time Center care**
Age 35-39	0.313	0.322	0.429	0.326	0.485
Age 40+	0.176	0.101	0.163	0.140	0.212
Medium educated	0.398	0.507	0.299	0.372	0.117
High educated	0.386	0.366	0.642	0.558	0.848
Non-Dutch	0.210	0.098	0.084	0.186	0.163
# of other children	1.142	1.058	0.900	0.814	0.670
Predicted hourly wage (logs)					
Female full-time	2.886	2.865	3.004	2.902	3.100
Female part-time	2.782	2.775	2.861	2.806	2.918
Observations	176	276	559	43	264

Table 6.3: Predicted Earnings of Mothers

Observed choice:	No employment	Part-time Non-center care	Part-time Center care	Full-time Non-center care	Full-time Center care
Part-time	16.489	16.434	17.404	16.760	18.093
Full-time	25.187	24.783	27.697	25.501	29.834
Observations	176	276	559	43	264

The main interest of this chapter lies in child care center characteristics; namely prices and quality. Within the Pre-Cool Survey, the surveyed mothers for whom center quality information is available are spread across 39 centers in wave 1 and 34 centers in wave 2. Wave 1 observations are made in the latter part of 2010 and 2011 while wave 2 observations are made in 2012. Prices are not available within the survey itself, but were collected instead from the centers' websites. Price information is collected from centers for which there are quality observations in the Pre-Cool surveys. There are only a few centers for which we could not find price information. In effect, price and quality are predicted using a similar sample of centers. Using these hourly prices, prices are imputed for the full sample using a Heckman selection model. The reduced-form price equations were fitted separately for wave 1 and wave 2. Since price data is not collected in the Pre-Cool survey, the available price data is mostly from 2012 with some observations being from 2013. Prices were adjusted to 2012 values using the rise in the maximum hourly price of child care that subsidies can be received for the estimation. After the estimation, the predicted prices are adjusted again to the year the observation is from, once again using the change in the maximum hourly price of child care used in subsidy calculation [4].

Dutch child care subsidies paid by employers and public funds are available for dual income families that use either the formal child care centers or guest parents (*gastouderopvang* which are similar to home daycare. The subsidies are available up to a maximum price set for each year and child care type. The subsidy rates for 2010, 2011 and 2012 are shown in figure 6.2. Centers are free to choose the price that they charge but most prices tend to be around the maximum price for which subsidies are paid. In the Pre-Cool sample, the highest center price was €7 in the year 2013 and the lowest was €5.5 when the maximum price was set at €6.46. We do not directly use net prices since the subsidies are income dependent and therefore endogenous to the labor supply decision. To identify the effects of net prices, a much

[4] Subsidies for child care centers were capped at the hourly price of €6.25 in 2010, €6.36 in 2011 and 2012 and €6.46 in 2013. A predicted price for a 2010 observation is multiplied by $6.25/6.36$.

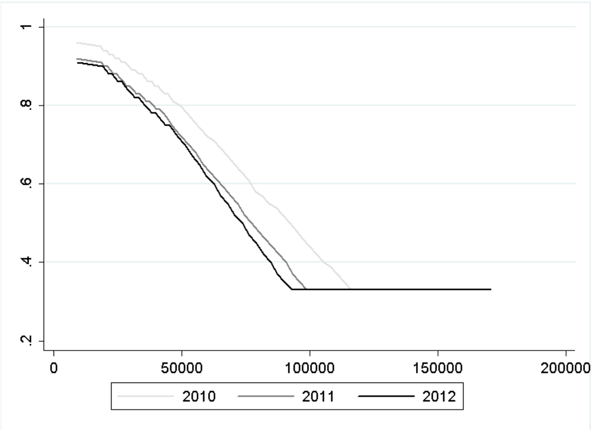


Figure 6.2: Daycare subsidies

larger dataset with households at the same income levels facing different gross prices is needed. Furthermore, since our data does not have specific information about whether other siblings are attending child care, net prices are not possible to compute correctly. Instead we use gross prices to estimate the elasticity. If we use prices that are adjusted for the flat part of the subsidy which is 33% for all dual income families up to the maximum hourly price cap for each year, the results remain similar.

Previous studies that explicitly look at the role of child care quality in determining child care demand and labor supply utilized the staff-to-child ratio and other observable attributes of child care that may influence the quality of early childhood education and care (ECEC) (Blau and Hagy, 1998; Hagy, 1998). However, these structural quality indicators are usually thought of as inputs to child care quality rather than quality itself (Blau, 1997). The indicator of quality applied in the present study is introduced by developmental psychologists to measure what is called process quality. Process quality measures are meant to provide an indicator for the quality of child-caregiver interaction and ECEC within the classroom. In case of Pre-Cool, process quality is measured by trained observers who visited the participating child care centers to grade their classrooms with the Classroom Assessment Scoring System (CLASS) (Howes et al., 2008). CLASS has previously been linked to child development and school readiness (Mashburn et al., 2008). The scale itself consists of seven dimensions which make up two domains: emotional support and instructional support. The emotional support domain consists of four dimensions: positive climate, teacher sensitivity, behavior guidance and regard for child perspectives. The instructional support domain is made up of three dimensions: facilitation of learning and development, quality of feedback and language modeling. Each dimension is graded during an observation on a discrete scale from 1 to 7. Scores above 5 are for high quality in a given dimension, in the range between 3 and 5 are average and below 3 are considered low. For the purposes of analyzing how child care quality influences labor supply, we construct an average quality indicator. We first take the average of the dimensions for emotional and instructional support domains and then use the mean of those two averages as average quality.

Table 6.4: Quality and Prices in the Netherlands

	Wave 1		**Wave 2**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Emotional Support	5.018	0.607	4.458	0.469
Instructional Support	3.092	0.730	2.628	0.508
Child to Staff Ratio	5.613	2.492	5.180	1.667
Predicted Price	6.507	0.211	6.533	0.216

The quality of child care in the Netherlands according to the Pre-Cool Sample can be seen in table 6.4 where predicted prices, child to staff ratios and averages of the instructional and emotional support domains are presented for both waves. The means for the quality measures are calculated over the classroom observations. Table 6.4 shows clearly that child care prices do not vary much in the Netherlands. This is unsurprising given that the subsidies are capped at a maximum hourly rate each year. Prices higher than the subsidy cap lead to large net increases for the parents. Prices with the highest prices in the Pre-Cool sample have hourly prices around € 7. In terms of quality, Dutch child care centers do well in emotional support, but rather poorly in instructional support. On average, Dutch centers do poorly compared to Finnish centers and are in range of American centers according to previous studies that employ CLASS (Howes et al., 2008; Pakarinen et al., 2010).

The estimations for prices and process quality in each wave can be found in Appendix 6B. To maximize the information used to predict quality and prices, we use all observations for which mothers' basic characteristics, price and quality data are available in each wave without limiting the sample due to missing values in male income and employment, female employment or male non-participation. None of the relationships with personal characteristics are consistently strong for quality or prices. However, province fixed effects appear to be strongly correlated with both price and quality levels in the second stage of the two step models, lending support to the argument that child care markets and the quality-price levels of formal child care differ between geographical locations.

6.4 Results

Using the predicted prices, wages, and quality, a mixed logit model with random coefficients for quality and wage variables is fitted. Having no employment is defined as the base category. The estimated coefficients of the model are shown in table 6.5. The covariance matrix of the random coefficients of quality, full-time and part-time wages is presented in table 6.6 and indicate that tastes with regards to child care quality and income vary significantly across individuals and there is significant unobserved heterogeneity in the sample.

Table 6.5 shows that the personal characteristics have predictable coefficients. More educated mothers tend to work more. Monthly income of the male partner and the number of other children have negative effects. Coming from a non-Dutch background has insignificant effects on full-time work but a negative effect on part-time work which might be due to the cultural preference for part-time work among Dutch women.

Wages and prices seems to have the expected positive and negative effects respectively while quality is insignificant. Several explanations may apply for the insignificant effect from quality. First, similar to prices, small differences in quality may not have a major influence on parents' child care and employment decisions. Alternatively, the results may be in line with the suggestion that parents are unaware of child care quality (Mocan, 2007). Information asymmetry would explain the small response from parents to different process quality levels. While parents may still desire high quality child care, their decisions will not be affected by process quality unless they can fully observe it. If quality is negatively correlated with other child care characteristics such as flexibility that parents value, this might explain lack of positive effects we find.

While the parameters are significant for prices and wages, they are not infor-

Table 6.5: Determinants of child care use and employment

Base category: No employment	Part-time Non-center care	Part-time Center care	Full-time Non-center care	Full-time Center care
Age 35-39	-0.7475	1.9040**	-2.1262	1.0396
	(0.8306)	(0.8919)	(1.4459)	(1.3436)
Age 40+	-2.1377*	2.1720*	-2.6737	1.001
	(1.1641)	(1.2650)	(2.0293)	(2.0393)
Medium education	1.8641*	3.1084**	3.6482**	2.5648
	(1.0129)	(1.2707)	(1.8554)	(1.7041)
High education	0.3889	6.9319***	3.2941	8.7790***
	(1.3591)	(1.7575)	(2.4674)	(2.4267)
Non-Dutch	-2.2193**	-3.1517***	0.4248	-1.0915
	(1.0809)	(1.1984)	(1.3205)	(1.5313)
Siblings	-0.0341	-0.3835***	-0.6467**	-0.9056***
	(0.1070)	(0.1010)	-0.272	(0.1401)
Male income 2000-3000	-0.7287	0.4782	-1.6214	-0.2218
	(0.7149)	(0.8207)	(1.0180)	(1.0325)
Male income 3000+	0.0544	-1.2705***	-0.9050*	-2.9791***
	(0.3434)	(0.4506)	(0.5341)	(0.6578)
Category-specific effect	-5.8817	11.227	-13.2909***	6.0835
	(3.8226)	(9.8811)	(4.6351)	(9.8994)
Predicted price	-	-2.8820**	-	-2.8820**
	-	(1.3385)	-	(1.3385)
Predicted wage	0.5467*	0.5467*	0.7494*	0.7494*
	(0.3181)	(0.3181)	(0.3829)	(0.3829)
Predicted quality	-	-0.0836	-	-0.0836
	-	(0.3836)	-	(0.3836)

*** p<0.01, ** p<0.05, * p<0.1. 100 Halton draws are used for the simulation.

Table 6.6: Covariance matrix of the random coefficients

	Quality	Part-time wages	Full-time wages
Quality	2.909***		
	(0.722)		
Part-time wages	-0.264***	0.126***	
	(0.108)	(0.039)	
Full-time wages	-0.175	0.085**	0.189***
	(0.141)	(0.034)	(0.045)

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

Table 6.7: Simulated Probabilities of Employment

	Observed	**Base**	**Wage +10%**	**Price +10%**
No employment	13.354	13.654	11.534	17.532
Part-time / center-care	42.413	42.742	41.433	31.108
Part-time / no center-care	20.941	20.240	20.691	24.950
Full-time / center-care	20.03	19.830	22.001	17.586
Full-time / no center-care	3.263	3.534	4.342	4.824

mative about whether the effects are economically significant. Using the estimated coefficients, we simulated four alternative scenarios to analyze the marginal effects of changes in prices and wages. For the base case, we simulated the probability of each category given the predicted earning levels and quality. In the second scenario, all wages are increased by 10%. In the third scenerio, all wages are increased by 10%. The simulated probabilities, along with the observed distribution of household choices are shown in table 6.7.

Raising both wages results in an overall participation elasticity with respect to wages of about 0.25. Our wage elasticity estimates is slightly smaller than the estimates from Norway by (Kornstad and Thoresen, 2007) and the US by (Herbst, 2010), who find estimates around 0.3. The size of our wage elasticity estimate is also smaller than other Dutch structural estimates by Bosch et al. (2013) who find elasticity values between 0.4 and 0.6 for women but within the range of estimates from other labor supply models (Meghir and Phillips, 2008).

Price appears to have a negative effect on employment and the elasticity of employment with regards to price is approximately -0.45. Center care use also declines while non-center care use rises especially among women in part-time employment. In the international context, there is a large range of employment elasticity estimates ranging from -1 to 0 (Blau and Currie, 2006). Our elasticity estimate is at the lower part of this range but is above other Dutch estimates. Previous studies on the effects of price in the Netherlands find either small or insignificant effects (Wetzels, 2005; Bettendorf et al., 2012). In general effects from prices tend to be small in Northern European countries such as Norway and Sweden (Kornstad and Thoresen, 2007; Lundin et al., 2008; Havnes and Mogstad, 2011a).

Several alternative specifications were fitted to check the sensitivity of the results.

Appendix 6C shows some of these alternative specifications. First, we fitted an alternative specific conditional logit model (ASCL) without random coefficients. Quality turns significantly negative in this case, suggesting that the heterogeneity of tastes towards child care quality plays an important role. Second, we omitted siblings from the model both in prediction equations and in the main model. The results remain similar as can be seen in Appendix 6C. Third, we used an unbalanced, larger sample of 1400 observations. Once again, the results shown in Appendix 6C are similar apart from stronger effects from wages. We also made a few minor specification tests by first omitting the male income variables from the main model which were not included in the prediction equations and then adding dummies for the second wave. The former test leads to slightly stronger effects from wages, while the latter slightly weaker. Price effect remains stable. Finally, to test the consistency of the main model, we calculated heteroskedasticity robust standard errors. Significance levels changed little.

6.5 Conclusions

Our analysis of Dutch women's labor market behavior leads to the conclusion that quality as defined by developmental psychologists does not positively affect women's labor supply behavior. The result is not in line with the standard economic theory that predicts a positive link between centers' quality and center based child care use and labor supply. The lack of effects may be due to the difficulty parents have in observing centers' quality. Alternatively, quality may be negatively correlated with other center characteristics such as flexibility that parents value. For the remaining variables, the effects are in the expected directions. Prices has the expected negative effect on labor supply while the wage elasticity of Dutch women with partners and young children is positive.

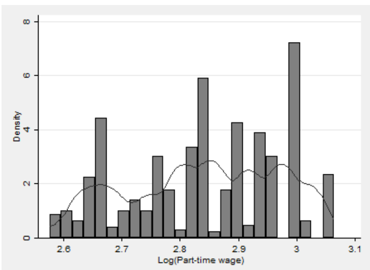
It is likely that research on ECEC quality and its determinants will continue regardless of its implications for labor supply. There is a growing policy and academic interest in ECEC quality and the benefits of high quality child care on future life outcomes. The impact of ECEC quality on development has already led to more investments in early childhood in both Europe and North America. An alternative reason to invest in child care quality could be effects on female labor supply, but we find no evidence of such effects. If we assume that the effects are lacking due to information asymmetry problems, more publicly information about the quality of child care centers may increase the returns from policies designed to increase ECEC quality by influencing labor supply.

6.6 Appendix 6A

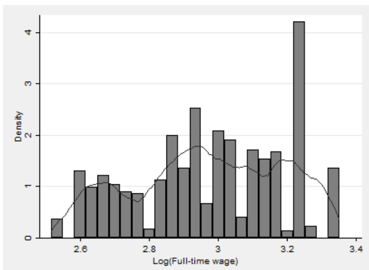
Table 6.8: OLS estimates for female full-time and part-time wages

	Employment status	
	Part-time	Full-time
Age 35-39	0.116***	0.225***
	(0.0112)	(0.0410)
Age 40+	0.181***	0.332***
	(0.0346)	(0.1150)
Non-Dutch	-0.0492	-0.093
	(0.0726)	(0.2309)
Medium education	0.0479**	0.0215
	(0.0196)	(0.0691)
High education	0.2210***	0.2775***
	(0.0248)	(0.0846)
Inverse mills	-0.0732	-0.0319
	(0.2494)	(0.8079)
Province controls	Yes	Yes
F-test provinces	11.25	2.97
Observed	10940	1232

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



(a) Part-time female wages



(b) Full-time female wages

Figure 6.3: Predicted Hourly Wages

6.7 Appendix 6B

Table 6.9: OLS estimates for quality and price

	Wave 1		Wave 2	
	Price	Quality	Price	Quality
Age 35-39	0.036	0.1282	0.0251	0.1390*
	(0.0498)	(0.1248)	(0.0504)	(0.0822)
Age 40+	0.1502***	0.1479	0.1477**	0.0745
	(0.0561)	(0.1420)	(0.0565)	(0.0928)
Non-Dutch	0.0841	-0.2804	0.102	0.125
	(0.1120)	(0.2736)	(0.1078)	(0.2238)
Medium education	0.0245	0.0018	0.0124	-0.1762
	(0.1119)	(0.2661)	(0.1089)	(0.1522)
High education	0.0554	-0.0209	0.0404	-0.1437
	(0.1131)	(0.2649)	(0.1094)	(0.1723)
Inverse mills	-0.1454	0.4513	-0.1752	0.1893
	(0.1580)	(0.3879)	(0.1458)	(0.3214)
Province controls	Yes	Yes	Yes	Yes
F-test provinces	13.82	9.89	13.72	4
Observed	138	151	138	135
All observations	812	812	812	812

*** p<0.01, ** p<0.05, * p<0.1. All observations indicates the number of observations in the selection equation (812) that also includes observations where price and quality are not observed.

6.8 Appendix 6C

Table 6.10: Alternative specific conditional logit estimates

Base category: No employment	**Part-time Non-center care**	**Part-time Center care**	**Full-time Non-center care**	**Full-time Center care**
Age 35-39	-0.1104	0.4045	-0.8090*	-0.0711
	(0.2728)	(0.2590)	(0.4840)	(0.3835)
Age 40+	-0.7697**	0.2497	-1.4009**	-0.5059
	(0.3843)	(0.3592)	(0.6732)	(0.5543)
Medium education	0.6816**	0.8241***	1.1469*	0.5414
	(0.2924)	(0.2961)	(0.6713)	(0.4434)
High education	0.1715	1.3961***	0.7902	1.6582***
	(0.4078)	(0.4019)	(0.7311)	(0.5301)
Non-Dutch	-0.6655**	-0.9262***	0.2857	-0.0432
	(0.2920)	(0.2659)	(0.4588)	(0.3058)
Siblings	-0.029	-0.3559***	-0.3975*	-0.8100***
	(0.1057)	(0.1014)	(0.2167)	(0.1348)
Male income 2000-3000	-0.0668	-0.4969**	-1.2152***	-0.2408
	(0.2110)	(0.2244)	(0.4261)	(0.2466)
Male income 3000+	-1.1632***	-0.3783	-0.8516*	-0.3747
	(0.3056)	(0.2592)	(0.4768)	(0.2990)
Category-specific effect	-2.0462	4.4277*	-5.7323***	1.802
	(1.6598)	(2.6144)	(1.3503)	(2.3487)
Predicted price	-	-0.8265***	-	-0.8265***
	-	(0.2880)	-	(0.2880)
Predicted wage	0.2108	0.2108	0.3782***	0.3782***
	(0.1403)	(0.1403)	(0.1139)	(0.1139)
Predicted quality	-	-0.3477**	-	-0.3477**
	-	(0.1371)	-	(0.1371)

Table 6.11: Mixed logit estimates without siblings

Base category: **No employment**	**Part-time** **Non-center care**	**Part-time** **Center care**	**Full-time** **Non-center care**	**Full-time** **Center care**
Age 35-39	-0.6677	2.1959**	-1.8198	1.505
	(0.9674)	(0.9540)	(1.6137)	(1.6603)
Age 40+	-2.6655**	1.9755	-3.5046*	0.7877
	(1.3103)	(1.2979)	(2.0928)	(2.1357)
Medium education	2.3478**	3.6299***	3.8643**	3.4188**
	(1.1732)	(1.2575)	(1.8199)	(1.5500)
High education	0.5997	7.1606***	2.9001	8.7395***
	(1.5199)	(1.7847)	(1.9994)	(2.2447)
Non-Dutch	-2.5593**	-3.2585***	0.0052	-0.8154
	(1.2116)	(1.1028)	(1.3050)	(1.3973)
Male income 2000-3000	-0.9536	0.1339	-1.9535*	-0.9214
	(0.8068)	(0.7975)	(1.0209)	(0.9860)
Male income 3000+	-3.6200***	-0.9971	-2.6499*	-1.0904
	(1.2963)	(1.0348)	(1.3864)	(1.2479)
Category-specific effect	-6.9968*	8.9943	-14.7191***	1.8329
	(4.0748)	(10.6754)	(5.1192)	(10.7986)
Predicted price	-	-2.8551*	-	-2.8551*
	-	(1.4853)	-	(1.4853)
Predicted wage	0.6463*	0.6463*	0.8869**	0.8869**
	(0.3438)	(0.3438)	(0.4055)	(0.4055)
Predicted quality	-	-0.0899	-	-0.0899
	-	(0.3993)	-	(0.3993)

Table 6.12: Mixed logit estimates with unbalanced sample

Base category: **No employment**	**Part-time** **Non-center care**	**Part-time** **Center care**	**Full-time** **Non-center care**	**Full-time** **Center care**
Age 35-39	-0.4029	1.7244**	-3.3595**	-0.1378
	(0.7826)	(0.8637)	(1.3790)	(1.2318)
Age 40+	-1.9152*	2.2731*	-4.5097**	-0.2258
	(1.0718)	(1.2148)	(1.9871)	(1.9441)
Medium education	2.0784**	3.9537***	3.8435**	3.7346**
	(0.8940)	(1.2170)	(1.9098)	(1.7023)
High education	0.4543	7.3490***	1.9165	7.8838***
	(1.1849)	(1.5976)	(2.2785)	(2.2700)
Non-Dutch	-2.8941***	-4.8241***	-0.4787	-2.0933*
	(0.9590)	(1.1594)	(1.2005)	(1.2460)
Siblings	-0.306	-0.6641***	-2.1578***	-1.8857***
	(0.2092)	(0.2079)	(0.4577)	(0.5002)
Male income 2000-3000	-0.9383	-0.1393	-2.1364**	-1.2564
	(0.6512)	(0.7741)	(1.0520)	(0.9315)
Male income 3000+	-3.0369***	-0.643	-2.0431	-1.3744
	(1.0401)	(0.9510)	(1.2481)	(1.1735)
Category-specific effect	-8.8062**	10.6314	-19.7824***	1.6024
	(3.6821)	(9.8145)	(4.5191)	(9.9365)
Predicted price	-	-3.3466**	-	-3.3466**
	-	(1.3455)	-	(1.3455)
Predicted wage	0.7128**	0.7128**	1.2277***	1.2277***
	(0.3099)	(0.3099)	(0.3632)	(0.3632)
Predicted quality	-	-0.1768	-	-0.1768
	-	(0.3785)	-	(0.3785)

Chapter 7

Summary and Conclusions

The empirical results we find throughout this thesis largely confirm and re-affirm theoretical models that treat parents as rational agents with limited information. Incentives provided by wages, child care prices and quality and parental leave entitlements have visible effects on parents' decisions. Where the results are less in line with what is expected from the rational choice models is when information plays a large role (Stigler, 1961). The degree to which parents are aware of the quality of child care they are purchasing might explain many of the effects found. The child care sector appears similar to other service sectors such as health care and schooling where information asymmetries play a large role in determining the workings of the market and consumer behavior.

To conclude the thesis, this section first provides a summary of the results found in each chapter. Afterwards, I discuss some policy recommendations that can be drawn. Finally, some future research areas are suggested based on the chapters.

7.1 Chapter Summaries

7.1.1 Chapter 2: Child care prices and female employment

The impact of child care prices on female labor supply is one of the first questions empirically analyzed after the introduction of family economics as a separate subfield. Since the study of female labor supply by Heckman (1974), a large literature has appeared that estimates the impact of child care prices (or subsidies) on female labor supply. The theoretical starting point is that a decrease in child care prices can decrease the opportunity cost of working for women. Despite generally relying on an unchanged static labor supply framework, the literature estimates for labor supply elasticity with regards to child care prices are varying. While some estimates imply substantial gains from child care subsidies, others find insignificant effects. Determining the reasons for the variance in the results and the settings in which elasticity estimates are smaller or larger is of substantial policy interest. If the elasticity estimates are large, child care subsidies may be a free lunch for governments that can recoup their expenditures through larger tax bases.

To understand the cause for variation among the elasticity estimates, this chapter reviews and analyzes the elasticity sizes using estimates from 39 studies. The chapter begins by reviewing the theoretical and empirical aspects related to participation elasticity with regards to the child care costs, paying special attention to sample characteristics, methodological aspects and institutional factors. We conclude by providing a meta-regression using control variables based on our review of the literature to explain some of the differences between the estimates.

Large differences in the target group used in the analysis or estimation methodologies seem to matter for elasticity sizes. The elasticity estimates tend to be larger for studies using subsamples of married women. More recent papers that use multinomial logit models tend to have smaller elasticity estimates than traditional probit or logit estimations. Most such models allow for substitution between the informal and formal child care which generally produces smaller elasticity estimates (Blau and Currie, 2006). Other improvements in methodology that are not explicitly controlled for may also account for the smaller elasticity estimates from studies published after 2000. There are many minor choices that differ across studies which we cannot control for such as how unobserved heterogeneity is modeled or whether choices regarding child care type and employment are simultaneously modeled.

The more striking finding is that the elasticity estimates are significantly correlated with labor market characteristics of the country that the estimation is from. Countries with very low participation rates tend to have smaller elasticity estimates. The effects may also diminish at very high participation rates. Countries with high working time flexibility through part-time employment also show lower elasticity estimates. Child care services do not seem to matter as much when part-time, informal substitutes are easily available. Although these findings are correlations rather than causal effects, they suggest that increasing child care subsidies in countries with very high female participation rates and opportunities for part-time employment do not have a large effect on the tax base.

7.1.2 Chapter 3: Parental leave and female labor market outcomes

The second chapter investigates the aggregate level effects of parental leave legislation on various labor market outcomes of women in 16 European countries for the period between 1970 and 2008. Parental leave legislation has changed substantially across all European countries in this time period and maternity leave is mandatory for all EU states since 1994. As a major family policy, the effects of parental leave have been studied before. This chapter builds specifically on the study of Ruhm (1998), who analyzed the effects of parental leave legislation on employment and wages in the manufacturing sector. The analysis extends and updates Ruhm's study by including a longer time period, more countries and analyzing effects on working hours, and wages in higher skill occupations.

One advantage an aggregate level study can have over micro level studies of parental leave is that the effects are estimated on all women rather than only mothers. Parental leave legislation affects not only mothers but also women who are likely to have children. Women may be more likely to enter into employment if they expect to have job security during maternity leaves while employers may be less likely to hire women who they expect may enter into parental leave. The methodological premise of the chapter is that the effects of changes in parental leave legislation on the labor market outcomes of women aged 25 to 34 can be identified through a difference-in-difference framework where men are used as the a control group. Since the countries in the analysis have large institutional differences, the DD model controls for country-specific and year-specific fixed effects as well as country-specific time trends.

Results show increases in participation rates that diminish with length and generosity of leave schemes. While pure participation numbers may not increase dramatically, there is strong evidence of increases in weekly working hours. On the other hand, longer parental leave schemes may lead to widenining gender wage gaps in high skill occupations, which is consistent with the idea that parental leave leads to glass ceilings for women. For wages in the low skill sectors, no effects are found.

7.1.3 Chapter 4: Child care quality and competition

The effects of competition and privatization have long been discussed and analyzed for schooling and health care but little is known about how competition affects quality in child care markets. In education sectors such as schooling and child care, there are at least two potential impediments to achieving perfect competition. First, the markets are relatively local, implying that there may not be many choices for parents. Having a single child care center in a town effectively results in a monopoly in the child care market of that town. The second impediment to perfect competition is information asymmetry. Parents may not know enough about child care quality to choose the highest quality center available to them even if the price remains constant across centers. This chapter empirically analyzes whether competition improves quality among child care centers in the Netherlands.

In the empirical analysis, the competition is measured by the average number of centers within 3 kilometers in the neighborhoods that the centers are located in. We make use of process quality assessments of the Pre-Cool survey to measure quality. There may be endogeneity concerns in OLS models even if center and area characteristics are controlled for. Centers with more child care centers may be operating in markets with low demand elasticities. To correct for endogeneity, we instrument the number of daycare centers in a neighborhood using the number of primary schools. Unlike child care centers, the number of schools is not dependent on child care demand characteristics of a neighborhood since schooling is mandatory. As an alternative instrument, we also use the lagged number of births to instrument competition.

The results show that high density of daycare centers in the area improves quality. The positive relationship found in the OLS models persists when either the density of primary schools or number of births in the area are used to instrument the density of daycare centers. The effects of competition are only show up for daycare centers when center and area characteristics are controlled for. When the same models are fitted for playgroups which do not function in a private market, the number of daycare centers in the neighborhood has no significant effects. Despite concerns about the parents' inability to distinguish between low and high quality child care, market competition in the Dutch child care sector appears to improve quality. Rather than a race to the bottom in terms of quality predicted by some as a result of privatization in the child care market, competition between centers seems to have the expected positive effects.

7.1.4 Chapter 5: Child care quality and subsidies

While earlier studies generally find positive effects from formal child care on child development, strong child development effects were not found in studies on the introduction of public child care in Norway and Canada (Baker et al., 2008; Havnes and Mogstad, 2011b) or child care subsidies in the United States (Herbst and Tekin, 2010). Child care quality may play a role in explaining the conflicting evidence on the impact of child care attendance on child development. Previous studies find that higher quality of care improves outcomes (Duncan, 2003; Vandell et al., 2010). If quality uniformly has a positive effect on development, it is important to understand how child care policies can affect quality. Reductions in child care subsidies that followed the fiscal consolidation in recent years may be risky if they lead to a reduction in quality.

This chapter studies the relationship between child care subsidies and the quality of formal child care. Exploiting the different types of child care funding in the Netherlands, we estimate the effects of a 2012 subsidy reduction on the quality of child care centers, again using process quality information from the Pre-Cool survey. Since subsidies are paid directly to parents, the cuts will have increased net prices which may have lowered demand for child care in daycare centers.

The subsidy cuts were for daycare centers while municipality funded playgroups remained unaffected and are used as the control group in our difference-in-differences model. We estimate the effects using both linear difference-in-difference and synthetic control models as well as non-linear changes-in-changes and threshold difference-in-difference models. The synthetic control model is employed to test whether the effects differ when playgroups with similar characteristics to daycare centers are given more weight in constructing the control group. The non-linear models allow us to take into account the shifts in the entire quality distributions of daycare centers and playgroups.

The results show that the subsidy reduction had a negative effect on centers' quality. The effects are robust to various specifications and appear to be driven by the decline in the middle of the quality distribution. This is in line with the view that centers have to lower quality in order to decrease prices for parents. We conclude that adjustments in subsidies not only affect access and affordability, but may also influence quality in child care markets.

7.1.5 Chapter 6: Child care quality and female employment

Chapter 2 shows that there is a large literature investigating the effects of child care prices on female labor supply. However, little is known about how child care quality influences labor supply decisions. Most theoretical labor supply models predict a positive effect from quality but the link is difficult to test empirically. Due to a lack of information, child care quality is often treated as a latent, unobserved variable in structural models estimating the effect of child care prices (Tekin, 2007).

In this chapter, we use the process quality measurements in the Pre-Cool survey to estimate the effects of child care quality and prices on female labor supply within a structural model. Using data of the Pre-Cool survey and the Labor Market Panel of the Statistics Netherlands, we predict child care prices, quality and wages for women using their personal characteristics and locations. The predicted values are used in fitting a multinomial logit model to estimate their effects on employment and child care type choices of married mothers. Similar to previous labor supply models, variation in tastes for income and child care quality are modeled using a random coefficient model.

The results indicate that the quality of child care available to mothers has no effects on their labor supply behavior. Prices and wages do have significant effects on labor supply in the expected directions. Increasing prices by 1% is expected to decrease employment by 0.35% and lower use of formal child care for working women. The uncompensated wage elasticity is approximately 0.5, which is in line with previous structural estimates for the Netherlands.

Unlike prices and wages, quality does not appear to influence parents' labour supply and child care choices. It is of course possible that parents simply do not care as much about the quality of child care they purchase. However, a more reasonable explanation for the lack of effects from child care quality on female labor supply may be information asymmetry. Unlike secondary schools, it is difficult to find information about the quality of child care centers. Such an explanation would be in line with the study of Mocan (2007) who finds that parents are uninformed about the true quality of child care they are purchasing.

The information asymmetry problem seems to result in a paradoxical situation in the child care market. The strongly significant and robust effects of competition on quality found in Chapter 4 may be due to centers competing on quality without realizing that customers are largely unaware of the quality of care they are purchasing.

This paradox may be called "self-fulfilling competition" since managers' assumption that parents care about child care quality and subsequent competition on quality is what drives the positive results found in Chapter 4. However, it is difficult to imagine that such an effect would be sustainable. If parents' do not respond to quality improvements among centers, the positive effect from competition might fade over time.

7.2 Policy implications

From the analysis, we can distil several policy implications. In this section, I discuss four general conclusions that can be drawn for policy making.

7.2.1 Implication I

Increasing child care subsidies is unlikely to have large labor supply effects. The meta-analysis in chapter 2 confirms the trend in the empirical literature linking child care prices and labor supply: the effects are diminishing over time. Recent studies, especially from Europe, find much smaller estimates of employment elasticity with regards to child care prices (Lundin et al., 2008; Bettendorf et al., 2012). The elasticity of employment with regards to prices presented in chapter 6 is comparatively large but uses a specific sample of mothers with very young children. Even the estimates from the United States, which were between 0.5 and 1 in the 90s (Kimmel, 1995; Averett et al., 1997) have become smaller over time (Herbst, 2010).

Undoubtedly, this is partly due to changes in estimation methods and improvements in methodology. However, institutional context and labor market characteristics appear to play a role as well. There is not much more to gain from lowering child care prices in most countries since they are low already. Meanwhile, the pool of mothers outside the labor force is becoming smaller.

7.2.2 Implication II

In parental leave legislation, a moderate length and generosity is optimal for labor market outcomes. Increasing parental leave lengths across EU countries may partly explain the smaller effects child care subsidies have on employment. Parents have the option to go on parental leave instead of using child care. In chapter 3 we investigated the aggregate level effects of parental leave legislation on various labor market outcomes of women in 16 European countries. The results indicate that a leave of 3 to 6 months of leave is optimal to increase labor supply without damaging women's wages and career prospects. Based on the labor supply effects alone, increasing the minimum maternity and parental leave entitlement across the European Union from its current level of 14 weeks is not very strong. Most of the benefits for female employment is in the first three months and there are strong negative effects from long leave periods on high skill wages. Longer parental leave of 6 months may however be useful in countries with a high incidence of part-time work since it raises working hours. The declining benefits from parental leave are also found by Thévenon and Solaz (2013), who use a similar methodology to estimate the effects of parental leave among OECD countries.

Clearly, parental leave legislation is not only about labor market outcomes. More generous parental leave has been linked with lower infant mortality rates (Ruhm, 2000; Shim, 2013). Furthermore, low fertility is a large concern for many European countries and parental leave entitlements can be an incentive to increase fertility (Gauthier, 2007). Given that parental leave seems to have effects on a variety of outcomes, its use for policymakers will depend largely on the context of the country.

7.2.3 Implication III

Policymaking in child care should focus more on children's development than parents' employment. Policy analysis tends to focus on female labor supply effects of child care, but effects of these policies on child care quality seems to be very real and perhaps more crucial than any labor supply effects. Even though labor supply effects are more easily observable in the short-term, development effects through child care quality are likely to be much larger in the long run. Chapter 4 shows that competition, brought about by the privatization of the daycare market in the Netherlands, can have positive effects on quality. Chapter 5 suggests that the reduction in subsidies for Dutch daycare has resulted in a reduction in quality. The conclusion in chapters 2 and 6 that further decreases in child care prices have little effects on female labor supply does not invalidate the use of child care subsidies as a tool to promote child development.

Even if child care quality had not been affected, a case for child care subsidies can be made through its effects on families' incomes. In Norway, Black et al. (ming) have found that while labor force participation effects of child care subsidies are limited, they can have large positive effects on children's development by increasing families' disposable incomes. As can also be seen in chapter 6, lower prices through child care subsidies are usually found to increase use of formal child care (Havnes and Mogstad, 2011a; Bettendorf et al., 2012), which would be worth incentivizing if child care quality is higher in formal centers.

7.2.4 Implication IV

The fundamental problem with the child care market is information asymmetry and information about centers' quality should be made more publicly available. If parents are unable to detect the educational quality of child care, large inefficiencies can arise from centers' competition over dimensions of child care that parents think signals high quality. In chapter 4, competition is found to have an impact on child care centers' quality, but the effects are not very large. In chapter 6, parents' labor supply and child care decisions are found to be influenced by relatively small differences in prices but not in quality.

The most obvious solution seems to be to make information about the educational quality of child care more easily accessible. Koning and Van der Wiel (2012) have found that publishing school performance indicators in national newspapers led to an increase in quality indicators of secondary schools that had low rankings. If effects are found for secondary schools, for which quality is already far more observable through graduation rates and grades, the child care market may benefit greatly from publicly available information on quality. Publicly available information would also ensure that positive effects from competition on child care quality do not fade as firms and managers become aware of the information asymmetry advantage they have.

7.3 Limitations and future research

As with any empirical analysis, more reliable data or simply more observations would improve the analysis throughout this thesis and data related weaknesses are discussed in the individual chapters. This section focuses instead on future research avenues that would take this thesis' chapters as starting points. Some policy questions are closely (or tangentially) related to what the chapters study and drawing conclusions for them without more evidence would be a mistake. In this section, three future research topics are discussed: 1) quality of non-center based child care and its effects on child development and labor supply, 2) effects of privatization on the child care sector and 3) subjective evaluation of quality and female labor supply.

An understudied and fundamental issue is how non-center care affects development and how its quality compares to that of center care. Bettendorf et al. (2012), Havnes and Mogstad (2011a) and Baker et al. (2008) all show that while employment is not strongly affected by child care subsidies, the child care use is. Increasing child care prices in simulations in chapter 6 has also shown stronger effects from prices on child care type than on employment. Higher spending on child care generally leads to less non-center care and more center care use. This substitution effect is generally treated as neutral since the main purpose of such spending is perceived to be increased female labor supply. However, if non-center care is of lower quality than center care, there may be positive development effects that are being ignored. Datta Gupta and Simonsen (2010) have shown that non-cognitive outcomes of children in Danish family day care (non-center care) is lower than in center care or home care. Unfortunately, very little is known about the quality of non-center care. Further field research on determining non-center care quality and analysis of how its quality is affected by programmes to subsidize non-center care would fill an important gap.

Chapter 4 analyzed the impact of competition on child care quality and found positive effects. An obvious, though potentially erroneous, leap to make is to conclude that privatization improves child care quality. Considering that privatization is on a number of countries' policy agendas for social services, studying its effects on child care quality and child development would be highly relevant. Multiple studies from different contexts would be especially useful since quality regulations in place are likely to affect quality (Hotz and Xiao, 2011). The most obvious method to study the impact of privatization would be to use policy changes, such as the Dutch Child Care Act in 2005 or the privatization of child care services in Florida between 2000 and 2002.

In chapter 6, no effects were found from process quality on female labor supply and center care use decisions. This may be explained by arguing that parents do not place much weight on child care quality or they do not observe child care quality. If the latter explanation is true, than we should be able to observe effects from quality as parents evaluate it. If subjective evaluations of child care quality is linked to labor supply decisions, making child care quality information publicly available would be especially relevant as a policy measure. Research in both development psychology and economics is teaching academics more about child development and the crucial role of child care, but it is unclear to what extent the primary stakeholders, parents, are aware of issues surrounding child development and what can be done to assist them in making the most optimal choices.

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Nederlandse Samenvatting

Deze dissertatie behandelt een aantal vraagstukken betreffende arbeidsparticipatie van vrouwen en de kwaliteit van kinderopvang. Om te beginnen wordt in hoofdstukken 2 en 3 ingegaan op de effecten van de prijs van kinderopvang en ouderschapsverlof op de arbeidsmarktparticipatie van vrouwen. In hoofdstukken 4 en 5 analyseren we hoe de kwaliteit van kinderopvang wordt beïnvloed door concurrentie op de kinderopvangmarkt en veranderingen in de kinderopvangsubsidies. In hoofdstuk 6 keren we terug naar de arbeidsmarktparticipatie van vrouwen en analyseren we hoe de kwaliteit van kinderopvang het arbeidsmarktgedrag van vrouwen beïnvloedt. Deze samenvatting geeft een kort overzicht van de onderzoeksvragen en de belangrijkste bevindingen van ieder hoofdstuk.

Er is uiteenlopend onderzoek naar de effecten van de prijs van kinderopvang op de arbeidsmarktparticipatie van vrouwen. Hoofdstuk 2 bespreekt en analyseert de prijselasticiteit van het arbeidsaanbod met behulp van een meta-analyse op basis van 39 studies. De meest opmerkelijke bevinding is dat de prijselasticiteit significant samenhangt met karakteristieken van arbeidsmarkten. Landen met een zeer lage of zeer hoge arbeidsmarktparticipatie van vrouwen laten over het algemeen een lage prijselasticiteit zien. Ook in landen met een flexibel arbeidstijdenregime is de prijselasticiteit van het arbeidsaanbod over het algemeen laag; kennelijk is de impact van de prijs van kinderopvang op het arbeidsaanbod minder groot wanneer informele alternatieven ruim voorhanden zijn. Hoewel deze bevindingen slechts correlaties laten zien, suggereren zij wel dat de hoogte van kinderopvangsubsidies slechts een beperkte invloed heeft op de arbeidsmarktparticipatie van vrouwen in landen met een hoge participatiegraad en met flexibele arbeidstijden.

Hoofdstuk 3 onderzoekt de effecten van ouderschapsverlof op de arbeidsmarktpositie van vrouwen in 16 Europese landen voor de periode van 1970- 2008. In deze periode is de wetgeving aangaande ouderschapsverlof aanzienlijk gewijzigd. Aangezien het hier een belangrijk beleidsdossier betreft, zijn de arbeidsmarkteffecten van verlof relatief vaak onderzocht. Dit hoofdstuk bouwt met name voort op de studie van Ruhm uit 1998, die de effecten van wetgeving betreffende ouderschapsverlof op werkgelegenheid en lonen in de industrie heeft geanalyseerd. De resultaten laten zien dat ouderschapsverlof een positief effect heeft op de arbeidsmarktparticipatie van vrouwen. Dit positieve effect wordt kleiner naarmate de lengte en generositeit van de verlofregeling toenemen. Hoewel het effect in absolute participatiecijfers relatief klein is, is het effect op het aantal arbeidsuren per week aanzienlijk. Uit de analyse blijkt bovendien dat een langdurig ouderschapsverlof leidt tot een verdere vergroting van het inkomensverschil tussen hoogopgeleide mannen en vrouwen. Dit is in lijn met het idee dat ouderschapsverlof het glazen plafond voor vrouwen versterkt. Voor laagopgeleiden zijn geen looneffecten gevonden.

In het onderwijs en in de gezondheidzorg zijn de effecten van concurrentie en privatisering veelvuldig bediscussieerd en geanalyseerd. Er bestaat echter nog weinig onderzoek naar het effect van concurrentie op de kwaliteit van kinderopvang. In hoofdstuk 4 staat de vraag centraal of concurrentie de kwaliteit van kinderopvang in Nederland verhoogt. Voor de analyses maken we gebruik van gegevens op het gebied van proceskwaliteit, afkomstig uit de Pre-Cool enquête. De resultaten laten zien dat er inderdaad een positief verband bestaat tussen concurrentie en de kwaliteit van kinderopvang: een hoge dichtheid van kinderopvangcentra in de directe omgeving van de kinderopvanginstelling heeft een positief effect op de kwaliteit. Het positieve verband blijft ook zichtbaar als we de dichtheid van kinderopvangcentra in de buurt instrumenteren door gebruik te maken van de dichtheid van basisscholen of het aantal geboortes in de buurt. De analyses tonen aan dat de dichtheid van kinderopvangcentra geen positief effect heeft op de kwaliteit van peuterspeelzalen. Dit is in lijn met het gegeven dat peuterspeelzaalwerk in Nederland niet als een private markt is vormgegeven. Ondanks dat er twijfels bestaan over de mate waarin ouders in staat zijn om de kwaliteit van kinderdagopvang te beoordelen, suggereren de uitkomsten dat er een positief effect is van marktwerking op de kwaliteit van kinderopvang.

Hoofdstuk 5 behandelt de relatie tussen kinderopvangsubsidies en de kwaliteit van formele kinderdagopvang. Gebruikmakend van het verschil in financiering van verschillende typen van kinderopvang in Nederland schatten we de effecten van een reductie van de subsidie in 2012 op de kwaliteit van kinderdagverblijven. Net als in hoofdstuk 4 zijn de schattingen gebaseerd op gegevens over proceskwaliteit. Omdat de subsidies rechtstreeks aan ouders worden uitbetaald, resulteert een verlaging van de subsidie in een stijging van de nettoprijs die de ouders moeten betalen. Naar verwachting leidt dit tot een daling in de vraag naar kinderopvang. De resultaten laten zien dat de verlaging van de subsidie een negatief effect heeft gehad op de kwaliteit van opvang. Deze bevindingen zijn robuust voor verschillende modelspecificaties en lijken te worden veroorzaakt door een daling van de kwaliteit in het middensegment van de kwaliteitsverdeling. Dit is consistent met de hypothese dat kinderdagverblijven de kwaliteit naar beneden bijstellen om de kosten te verlagen. We concluderen dat aanpassingen in het subsidieregime niet alleen de toegang tot en de betaalbaarheid van kinderopvang beïnvloeden, maar mogelijk ook de kwaliteit van kinderopvang.

Hoofdstuk 2 heeft laten zien dat er veel onderzoek is gedaan naar de effecten van de prijs van kinderopvang op de arbeidsmarktparticipatie van vrouwen. Niettemin is er weinig bekend over de invloed van de kwaliteit van kinderopvang op het arbeidsaanbod van vrouwen. In hoofdstuk 6 maken we opnieuw gebruik van de proceskwaliteitsmaatstaven uit de Pre-Cool enquête om de effecten van de kwaliteit van kinderdagopvang op de arbeidsmarktparticipatie van vrouwen te schatten. De resultaten laten zien dat de kwaliteit van kinderopvang geen effect heeft op de arbeidsmarktparticipatie van moeders. Lonen en prijzen laten wel een significant effect zien en hebben bovendien het verwachte effect op het arbeidsaanbod: lonen hebben een positief en prijzen een negatief effect. Het is mogelijk dat ouders simpelweg weinig waarde hechten aan de kwaliteit van de kinderdagopvang. Een meer waarschijnlijke verklaring voor het ontbreken van een effect van kwaliteit van kinderopvang op arbeidsmarktparticipatie van vrouwen is evenwel het bestaan van informatie-asymmetrie. In tegenstelling tot bijvoorbeeld middelbare scholen is het moeilijk om informatie te vinden over de kwaliteit van een kinderdagverblijf. Een dergelijke verklaring is in lijn met de studie van Mocan (2007), die laat zien dat ouders weinig informatie hebben over de werkelijke kwaliteit van het kinderdagverblijf.

Curriculum Vitae

Yusuf Emre Akgündüz (1987) was born in Istanbul and completed his high school education at the American International School of Rotterdam with an International Baccalaureate diploma. Afterwards, he received his Bachelor degree in economics from the Utrecht University. In 2009, Emre completed the Economics and Social Sciences programme with cum laude to receive his Master of Science degree at the same university. He became a PhD candidate in 2010 in the Utrecht University School of Economics within the Coordinating Societal Change programme of the Utrecht University. His areas of interest are labor economics, family economics and child care provision. Emre attended a number of conferences and summer schools during his studies at the Utrecht University including the IZA Summer School, EALE and ESPE. He also published several articles in international journals and working paper series during his PhD.

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