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Evaluation of Classical Monopsony in Nursing Labor Markets: A Natural Experiment

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ABSTRACT. Taking advantage of the fall and rise of the private maternity ward BB Sophia (2014–2016) in Stockholm, Sweden as a natural experiment, we used administrative payroll panel data from 2010–2018 with all publicly employed nurses in Stockholm County to evaluate classical monopsony models in nursing labor markets. Previous studies in nursing labor markets have evaluated the effect of legislated changes in staffing (salary) on salary (staffing), respectively, with mixed results. Here, we propose a novel strategy by utilizing changes in employer concentration to estimate effects on salary and employment. We employed a difference-in-differences approach with individual fixed-effects using inpatient midwives as treatment group and non-affected nursing categories as control. Based on the dominant firm and competitive fringe monopsony model for entry and exit of maternity wards, our results support that salary for inpatient midwives and employment overall for midwives increase in conjunction with decrease in employer concentration. However, employment decreased for public sector employers, questioning underlying assumptions on the shape of the fringe demand curve and limitations in short-term labor supply in the classical monopsony model that predict higher employment even in the public sector.

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Concepts and definitions

Registered nurses	Registered nurse – licensed nurses that have not specialized or do not work at specialist nurses (“legitimerad sjuksköterska”)
Specialist nurses	Specialist nurse – licensed nurses that have additional training and are employed as specialist nurses (“specialistsjuksköterska”). For our purposes, we include midwives here as well.
Nurses	Both registered nurses and specialist nurses
Nursing Categories	Different specialist nurses as separate csategories and registered nurses as a category by itself
Midwives	Registered nurses that have specialised to become midwives.
Statistics Sweden	Governmental agency (“Statistiska Centralbyrån, SCB)
The National Board of Health and Welfare	Governmental agency (“Socialstyrelsen”)
The Swedish Association of Health Professionals	Labor union for health professionals, including nurses. (“Vårdförbundet”)
The Swedish Association of Midwives	Labor union for midwives. (“Barnmorskeförbundet”)

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1 Introduction

The shortage of nurses is arguably the largest and most-discussed public policy issue currently in Sweden (Rising 2018). At its peak in the spring of 2018, almost a third of all hospital beds in Stockholm were closed (Weilenmann 2018), elective surgeries had been postponed resulting in inpatients being sent to other countries (Mahmoud 2018), and patients had to wait for a hospital bed in the emergency clinic for days – all due to the nursing shortage. While the Swedish healthcare system may be unique in terms of being hospital-heavy, the nursing shortage is a chronic problem that exists in a multitude of countries, including the US and UK.

Numerous studies have aimed to understand the underlying mechanisms in the nursing labor market, in part as an effort to help guide policy efforts. One of the leading theories for explaining the nursing shortage is that employers in nursing markets hold monopsony power. In broad strokes, a monopsony entails that a single or a group of employers have significant market power, analogous with a monopoly but for employers vis-à-vis employees. Due to a decreased ability to wage discriminate, this leads to an upward sloping supply curve, which leads to a market equilibrium with a lower wage and employment level. Critically, increased wages are therefore associated with increased employments levels and vice versa. The theory has been used to explain why there may be a nursing shortage even when there is not a shortage of labor with nursing training.

The labor market for nurses is often used in textbooks as the quintessential example of a monopsony, yet empirical studies have so far been contradictory. The bulk of previous research has compared different regions with different market employer concentrations with mixed results, in no doubt due to the significant endogeneity problem due to wages and employment levels being set simultaneously. A handful of studies have used either the introduction of minimum-wage or minimum nursing-levels as instruments. However, they have been limited by short study periods and difficulties in finding suitable control groups and have had contradictory results.

Here, we propose a novel approach, using changes in employer concentration to study effects on salary. This approach takes advantage of a natural experiment arising from the opening and closing of the relatively large maternity ward BB Sophia in 2014 and 2016 respectively, as well as the simultaneous closure of Södra BB in 2016, both in Stockholm, Sweden.

We use a panel dataset based on administrative payroll data containing all nurses and specialist nurses employed by the public healthcare sector in Stockholm, Sweden from 2010 to 2018. Using a difference-in-differences approach with fixed-effects, we show that inpatient midwives compared to the control, intensive care nurses, experienced a salary increase of 0.35% ($p<0.01$) when BB Sophia was open, and a 0.38% ($p<0.001$) salary decrease after the closing of both maternity wards. While these results may indicate monopsonistic forces, we discuss several alternative interpretations, which may be especially important considering the small magnitudes.

We limit ourselves to empirically evaluating evidence for classical monopsony. Additionally, since we are using individual salary trends and only have data of those employed in the public sector, we will only be able to evaluate wage trends for those that are and remain employed by the public sector during the study period. Furthermore, we will not consider other labor market models, nor their ability to explain our findings.

This thesis is organized in seven additional parts: Section 2 presents a review of previous research, Section 3 introduces the theoretical framework for monopsony, and Section 4 describes our econometrical specification and approach. Subsequently, Section 5 details qualitative data and Section 6 presents the panel data set with descriptive statistics.

Section 7 presents regression results on wage and descriptive data on employment, Section 8 discusses interpretations of the results and presents sensitivity analyses. Section 9 contains concluding remarks and proposes future studies.

2 Previous research

Previous research has used monopsony to explain phenomena in the labor market that are inconsistent with competitive labor markets. For example, monopsony has been used to explain unaffected employment levels at the introduction of a minimum wage (Card and Krueger 1995, as cited in Staiger, Spetz & Phibbs 2010 p. 212). Details of classical monopsony are presented in section 3.

Models with monopsonistic features have been used in attempts to explain a number of phenomena, including racial pay gaps (Bhaskar, Manning & To 2002), gender pay gaps (Manning 2003), dispersion in wages for equal professions (Bhaskar, Manning & To 2002), the effect of firm size on wages (Boal, Ransom 1997) and the varying effect on employment at the introduction of a minimum wage (Bhaskar, Manning & To 2002; Bhaskar, To 1999; Dickens, Machin & Manning 1999).

While nursing labor markets are literally the textbook case of classical monopsony, there has been substantial difficulty in demonstrating this in empirical studies. In the following sections, we summarize the bulk of previous research on monopsony and the labor market for nurses. First, we explore the literature of more traditional cross-sectional studies, and then quasi-experimental approaches. After that, we return to Sweden, where there is considerably less research.

2.1 Cross-sectional studies

By far, the most common type of study has been cross-sectional studies that compare different areas with different employer concentrations directly with nursing wages. Richard Hurd (1973) was first to do so, and showed strong negative correlation consistent with a monopsony. Several other studies followed suit, including Link and Landon (1975) and Feldman and Scheffler (1982), with results in the same direction.

However, several critics (Hirsch, Schumacher 1995; Sullivan 1989) comment on the substantial endogeneity problem with such study designs, naming several reasons for there being higher wages for markets with higher market concentrations: living cost differences, higher alternative occupation salaries (alternative costs), and perhaps higher skilled workers in metropolitan areas compared to less-densely populated areas. Some further issues in select studies may be due to limitations in data, which in turn lead to questionable assumptions. These include questions on whether characterizations of market concentration are accurate in studies that group data from varying years, as well as discrepancies between studies on how market concentration is characterized at all.

One highly praised study (Hirsch, Schumacher 1995; Sullivan 1989) that stands out is Adamache and Sloan (1982), which after controlling for cost of living, find no evidence of effect on entry-level wages. Taken together with previous studies of similar design, the results are interpreted as inconclusive.

Another well-cited study is by Hirsch and Schumacher (1995), that used census data from the Current Population Survey Outgoing Rotation Group, containing monthly data stretching from 1985 to 1993 in the US. One key contribution is that they used a control group, namely female non-nursing professions, separated into three educational levels. They argue that this is a better characterization of regional differences and better captures non-measurable differences in cost of living, overall quality of labor, working conditions, among other potentially omitted variables. Their results show no relationship between market concentration and nurses' wages. Limitations of their study include that there may be some overlap in their labor markets, but primarily in their control group, which they also discuss in their paper. Issues with their control group was further scrutinized by more recent publications at the Institute for Evaluation of Labor Market and Education Policy in Sweden[1] (Hanspers, Hensvik 2011).

The other common research question using a cross-sectional study design is to determine labor supply curve elasticities in nursing labor markets. Frequently cited examples are Sloan and Richupan (1975), Link and Settle (1979), and Hansen (1992). One such study that deserves additional attention is Sullivan (1989), which used survey data from the American Hospital Association's Annual Surveys of Hospitals from 1979 to 1985 to estimate inverse elasticity of labor supply. Using caseloads and length of hospital stay at individual hospitals as an instrument, Sullivan (1989) estimated the inverse elasticity of labor supply. Given a constant marginal product, the inverse elasticity of labor is related to the percentage difference between wage and marginal product, and therefore also the wage difference compared to a competitive labor market. Using three approaches to the market equilibrium, Sullivan concludes in estimates that show evidence for substantial monopsony power for hospitals. However, results are similar for both metropolitan and non-metropolitan hospitals, which is surprising.

Other researchers, notably Hirsch and Schumacher (1995), argue that while studies that determine labor supply curve elasticities may provide evidence for upward sloping supply curves, they are not conclusive on whether labor markets are monopsonistic. That is, there may be numerous other reasons for why supply curves are upward sloping, such as hospital-specific training, and/or explicit or implicit back-ended compensation incentive contracts.

As major strengths of cross-sectional studies include large sample sizes (up to hundreds of regions or hospitals), they certainly have their

[1] A part of the Swedish Ministry of Employment.

role in the scientific literature. However, despite ambitious attempts at various control methods, cross-sectional studies are prone to endogeneity problems and potential reverse causality that are difficult to compensate for. As such, in the next section we will discuss more recent literature that utilize a quasi-experimental study design that has potential to mitigate many of the above-mentioned problems with cross-sectional studies.

2.2 Quasi-experimental studies

While monopsony in nursing markets have been a popular research topic, there has been a paucity of quasi-experimental studies up until the last decade. As previously mentioned, the key feature of monopsony is that employment levels increase with wage. However, wages and employment levels are set simultaneously, and an instrumental variable is needed in order to study their effects on each other (Matsudaira 2014). Although Sullivan (1989) used length of hospital stay and caseloads as an instrumental variable, we grouped his work with the other cross-sectional studies above as it did not utilize a more structured exogenous change, as the studies do in this section.

Phibbs et al. (2010) utilized a legislated wage change in nursing wages at Department of Veteran Affiairs (VA) hospitals in 1991 for testing the effects of an exogenous wage change in nurses' labor market. The legislated change allowed for VA hospitals to change nursing wages from a national pay scale to a regional wage based on surveys of nearby hospitals. Their sample comprised data from about a thousand hospitals (the number differs between analyses) on registered nurses' wages, starting wages, patient caseloads, staffing levels and other hospital characteristics. The data was first-differenced to control for unobserved hospital features and cost of living, and included one year prior to the wage change and one year after (1990–1992). Using the distance from a hospital and their closest VA hospital, the authors studied the effects of VA wage change on neighboring hospitals and found that the closest neighbors responded the most and that the effect diminished for more isolated hospitals. Using the legislated wage change as an instrument, they also estimated labor supply elasticities. Their estimates on short-run elasticities came in at about 0.1, implying that marginal revenue product for nurses is much higher than their wages. Taken together, the conclusion was that their study showed some evidence for monopsony.

Major limitations to the study are that it is questionable whether the legislated wage was truly exogenous, as there may have been underlying confounders that was already driving nursing wages, that may be geographically biased towards locations suitable for VA hospitals. As VA hospital wages were set relative to the wages of nearby hospitals, increasing salaries in VA hospitals may be capturing trends in rising nursing wages in that area. While the analyses controlled for local wage trends, the 3-year study period may not have allowed for sufficient control for lagged effects, which may be particularly relevant since wages were set according to (past) surveys of nearby hospitals. Certainly, a negative control group may have mitigated some of these limitations. Another important limitation also mentioned by the authors is that this change applied to VA hospitals only, which may be substantially differentiated from other hospitals, contributing to monopsonistic effects, limiting the study's generalizability to regions with more homogenous hospitals. Furthermore, the 3-year study period did not allow estimates for more long-term effects.

Matsudaira (2014) instead used a legislated minimum staffing law in Californian nursing homes in 2000 as a natural experiment. The study looked at changes in wage levels three years post policy introduction. Wages appeared not to increase with increased staffing levels, in fact employers seemed able to recruit at the market wage at all times throughout the study.

Several major limitations are mentioned by the author, and there is also a number of significant differences to the above study by Phibbs et al. (2010). While Phibbs et al. (2010) had detailed information including seniority of nurses and investigated starting salary, Matsudaira (2014) did not control for the seniority of nurses and instead used firm-level wages. Furthermore, while Phibbs et al. (2010) looked at wages at hospitals for registered nurses, Matsudaira (2014) studied nursing aides at nursing homes, a significantly different population. In this case, it is reasonable to assume that nursing aides have significantly greater heterogeneity in qualifications and skill levels than registered nurses. In combination with lack of variables controlling for experience, this heterogeneity may lead to systematic hiring of "less skilled" nurses, while keeping wages at the same level, a scenario also discussed by the author.

Taken together, a couple of studies have utilized natural experiments to study nursing labor markets and monopsony power in nurse employers. However, results are contradictory, which perhaps may be explained by differences in the study populations and designs.

2.3 Studies in Sweden

The empirical base is smaller in Sweden, but a few studies that focus on employers' market power should be mentioned. One of them points out collusive behavior among four big Swedish companies as an act to suppress civil engineers' wages (see Jakobsson 1999, cited in Calmfors, Richardson 2004 p. 34).[2] Another study that addresses monopsony looks to the increased competition in five Swedish labor markets, namely the markets for: preschool, school, elderly care, taxi and restaurants (Hanspers, Hensvik 2011). Wages were found to have decreased in the market for taxis, remained unchanged for elderly care and preschool, but increased in the school sector as markets experienced increased competition. The school sector in Sweden had been deregulated

[2] ABB, Ericsson, Saab-Scania and Volvo are cited as examples.

previously, which led to private actors entering the market alongside public providers of education. As salaries primarily went up for labor that decided to stay at public schools, the authors drew the conclusion that the employers previously held some wage-setting power, consistent with monopsony. Importantly, the Swedish labor market is generally more regulated than the US counterpart, as evidenced by stronger labor unions and less fluid labor markets.

2.4 Monopsony and union power

Many studies evaluate the effect of union power and monopsony (Adamache, Sloan 1982; Feldman, Scheffler 1982). It is important to note that as labor unions have substantial legislated power in Sweden, many of results from studies in the US are not readily generalizable to the Swedish labor market, and vice versa.

2.5 Our contribution

Our study, in many ways, remedies some of the largest challenges faced by previous studies in this field. Firstly, we do not use a cross-sectional study design, which has been scrutinized for endogeneity problems. Secondly, we directly estimate effects on wage and not labor supply curve elasticities, which have been argued to be necessary but not sufficient to show monopsonistic conditions. Furthermore, we use panel data that allows for individual fixed effects. Thirdly, we uniquely use, arguably, the best possible control group, i.e. other nursing categories in the same city, employed at the same hospital/clinics that are not affected by the employer concentration change, while other studies have used non-nursing female professions or no control at all. Fourthly, we use a market entry as well as an exit, which allows for two events to be analyzed.

3 Theoretical framework

In this section, we introduce a simple model of classical monopsony, where only labor and capital enter a firm's production function. We will first briefly outline the competitive labor market model, to illustrate key differences in the monopsonistic model.

3.1 Brief summary of a competitive labor market model

In a competitive labor market, firms are not wage-takers and not wage-setters, i.e. they do not affect the wage in the market. The equilibrium wage and quantity is the intersection of firms' demand for labor and the supply of labor. Consequently, the labor supply is theoretically perfectly elastic.

3.2 Classical Monopsony

In our example of a classical monopsony, we assume that capital is acquired in a competitive market and that it is fixed in the short run, which allows for the creation of a static model where only wage and amount of labor is considered.

In a classical monopsony with only one employer, they will be unable to wage discriminate and has to pay the same wage to everyone.[3] As exemplified by Blair and Harrison (2010): any efforts to offer higher wages to new hires, will cause existing employees to quit and be rehired at a new, higher wage. As everyone in the classical monopsony is paid the same wage, the marginal factor cost of labor is composed of two parts – the increased salary for the new hires and the increase in salary for the rest of the employed labor (1).

$$MFC = w(L) + \frac{Ldw(L)}{dL} \tag{1}$$

[3] We will disregard the case of a discriminating monopsony, as the monopsony in that case would not show characteristics of labor shortage (Hirsch, Schumacher 1995).

This results in firms facing an upward-sloping labor supply curve, which is a key feature of the monopsony.

As touched upon above, a competitive labor market settles on an equilibrium where the supply and demand curve meet. Similarly to a competitive market, a monopsonistic employer maximizes profits by hiring labor until the marginal revenue of labor equals the marginal factor cost of labor. However, since the labor supply curve is upward-sloping, the marginal factor cost of labor in the monopsony (2) is higher than in a competitive market (3). Therefore, the equilibrium is settled at a lower wage and employment rate. The equilibrium is *not* where the supply curve meets the demand curve.

$$MFC = w(L) + \frac{Ldw(L)}{dL} \tag{2}$$

$$MFC = w \tag{3}$$

As illustrated graphically below, in the monopsony, marginal factor cost of labor equals marginal revenue product of labor in an intersection further up the curve than the intersection of the labor supply curve and the marginal revenue product curve. From this point, the quantity of labor supplied can be read by tracing downwards to the labor supply curve (Q_m in Figure 1). At this quantity, labor will work for wage W_m. A monopsonistic labor market may be presented the following way:

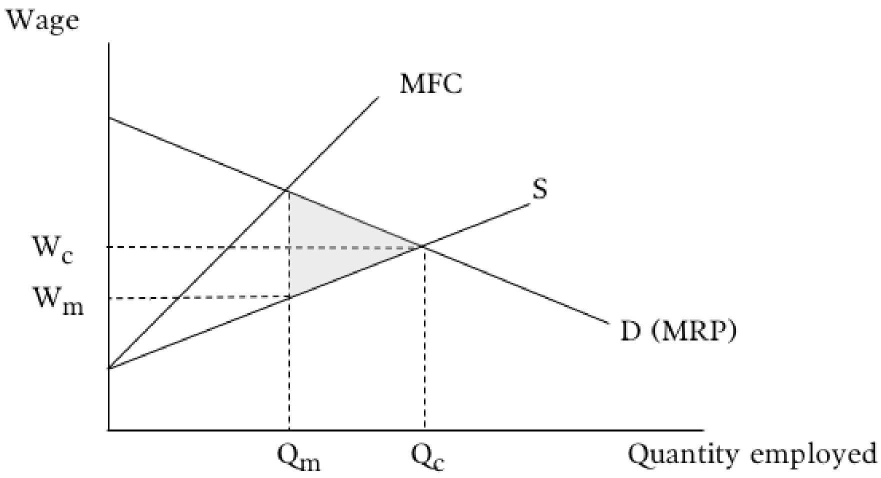

Fig 1. Classic monopsony compared to perfectly competitive labor market.

In the monopsony, firms will not hire the competitive quantity of Q_c workers at the competitive wage W_c. Rather, the employment will fall short of the competitive quantity at a lower wage, such that:

$$Q_m < Q_c \tag{4}$$
$$W_m < W_c \tag{5}$$

The implications of the simple monopsony model are that the firm will hire fewer workers than under competitive conditions (4), at a wage lower than if competitive conditions prevailed (5). This creates inefficiency, or economic welfare losses, represented by the shaded triangle in Figure 1.

A classic example of a real-life monopsony is a mining town, where one employer hires workers with few or no feasible alternatives. However, as previous researchers stress, one should not be restricted to a too narrow interpretation of the concept. One way of perceiving the monopsony is recognizing that there are possible situations in which employers have important market power (Manning 2003).[4]

3.2.1 The effects of decreased market concentration

We will now consider the implications for wages and quantity of workers employed following a decrease in employer concentration in a monopsonistic market. As employer concentration decreases, monopsony power previously held by the firm(s) is diminished. The more the concentration is reduced, the more the market approaches the competitive equilibrium (Calmfors, Richardson 2004). The relationship between market concentration and wages and employment is therefore negative. In contrast, in a perfectly competitive market, individual firms are wage-takers and there should be no difference in wage due to a new market entry.

One model for simulating a new entry is the model of a dominant employer and a competitive fringe (Blair, Harrison 2010), see Figure 2, top.

[4] Manning is one of the dominant voices in this strand of research, arguing for the stressing this fact.

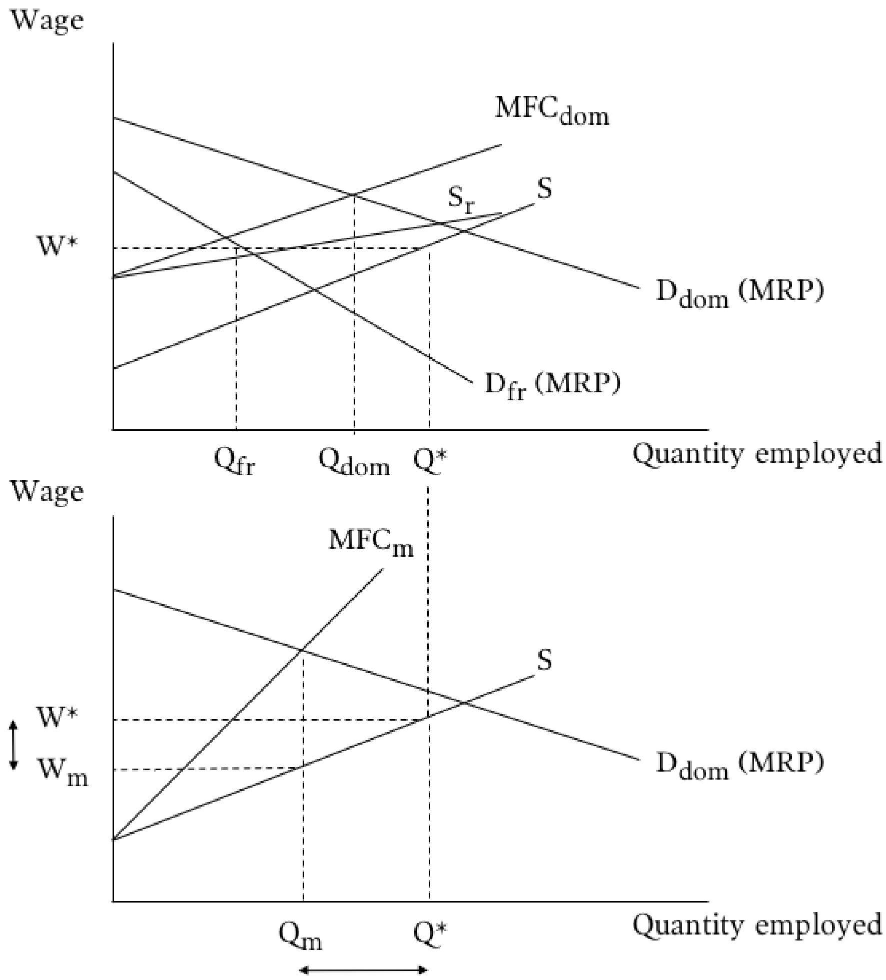

Fig 2. Dominant firm with competitive fringe (top) compared to monopsony (bottom).

In this model, the competitive fringe (or simply fringe) is the new entrant to a previously monopsonistic market, and the dominant employer is the monopsony. It is assumed that the dominant employer has some cost advantages, perhaps due to economies of scale, know-how, or other competitive advantages. Furthermore, the fringe is a smaller competitor (or comprised of smaller competitors) and therefore employs fewer workers at a given wage. Therefore, the demand curve of the fringe (D_{fr}) is steeper compared to the dominant firm (D_{dom}). At any given wage, the fringe will employ a smaller quantity than the dominant firm.

Since the dominant firm needs to consider the demand of the fringe, it subtracts the demand curve of the fringe from the labor supply curve which gives the new residual labor supply curve (S_r), from which a new, flatter MFC curve can be derived.

Comparing the dominant firm model versus the monopsony (Fig 2), we see that also the dominant firm employs more labor at a higher wage when there is a fringe, compared to pure monopsony. This is because the marginal factor cost of labor is less, making it cheaper to employ additional labor. As the demand, and therefore also the MRP, is the same, the new equilibrium is established at W*, Q_{dom} for the dominant firm. Furthermore, since the fringe also employs labor at Q_{fr}, the total number employed in the market is even greater. Therefore, this model predicts that both wage and employment levels increase with a labor market concentration drop (Blair, Harrison 2010).

In summary, the monopsonistic model predicts higher wages and employment in the case of new entry of a competitor compared to a competitive labor market and vice versa for market exit.

3.3 Research question

How does changes in employer concentration affect nursing salary? We define our labor market as centrally located healthcare providers in Stockholm, Sweden, excluding Norrtälje and Södertälje hospitals. Also, we limit ourselves to study the effect on salary in publicly employed nurses during the period 2010–2018, and in particular the change in employer concentration caused by the opening of BB Sophia and the closing of BB Sophia and Södra BB.

3.3.1 Hypotheses

Our perception of the public labor market for nurses in Stockholm is conceptualized by the dominant firm with competitive fringe. Public sector healthcare as well as private sector healthcare is financed by the Stockholm County Council ("Stockhoms Läns Landsting"). Given that public sector workplaces have many similarities in contracts and financing, we regard them as one entity in our model. Although we recognize employers may be differentiated in ways that are important to the workforce, we do not consider this in our model. Public sector employers are thought of as the "dominant firm", and BB Sophia is the "competitive fringe", when they enter the Stockholm maternity care market in 2014. Considering that the opening of BB Sophia decreases employer concentration, and near-simultaneous closing of BB Sophia and Södra BB increases employer concentration, we deduce the following two hypotheses for nurses employed in the public sector:

(1) Relative salary development will be **higher** for nursing categories employed by BB Sophia compared to non-affected nursing categories during the years BB Sophia was open, compared to before BB Sophia was open

(2) Relative salary development will be **lower** for nursing categories employed by BB Sophia/Södra BB compared to non-affected nursing categories employed by public sector in Stockholm, after the closing of BB Sophia/Södra BB, compared to when they were open

4 Method

In this section, we introduce our study design, the econometrical specification, and describe different considerations for our chosen method.

4.1 Difference-in-differences estimation

To measure the effect on salary for affected nursing categories versus non-affected nursing categories, we will use a difference-in-differences estimator and regress on the logarithm of nominal salary on an individual level:

$$\log(salary)_{it} = \beta_0 + \beta_1 treat_i + \beta_2 time_t + \rho(treat_i * time_t) + X_{it} + \delta_i + \varepsilon_{it} \qquad (6)$$

where i is individuals and t is time; *treat* is a dummy which is 1 for affected nursing categories and 0 for non-affected nursing categories; *time* is a dummy that is 1 for the time of interest; ρ is the estimator for the effect of treatment (opening of BB Sophia/closing of BB Sophia and Södra BB). Furthermore, X_{it} is a set of control variables, δ_i are individual fixed-effects, and ε_{it} is the error term.

As a set of control variables, time-dependent covariates are added in more detailed specifications. These include age, whether the nurses are permanently employed, working hours, whether they work full-time or part-time, as well as year effects. Age is an important covariate, as age is a proxy for seniority and is expected to be associated with increased salary. Furthermore, permanently employed nurses may have differential salaries compared to temporarily employed nurses, as they are not covered by the same labor union contracts. Working hours, whether nurses work normal office hours only, or also evenings, or night shifts may also be reflected in salary. As salaries are recalculated into full-time equivalents, part-time wages may not directly correspond to full-time wages, warranting for this to be controlled as well. Year effects aim to capture any potential affects that may affect all nurses employed by Stockholm County Council. To further reduce omitted variable bias, we will use individual fixed-effects.

Affected nurses are nursing categories that were employed by BB Sophia. Non-affected nurses are nursing categories that were not employed by BB Sophia but otherwise had similar labor market conditions. Treatment and control groups were selected in a systematic fashion as detailed below.

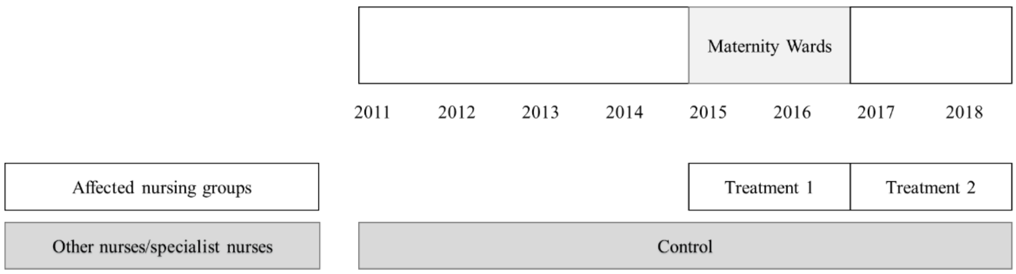

Fig 3. Depiction of the difference-in-differences approach

4.1.1 Opening of BB Sophia

BB Sophia started recruiting September 2013, and opened officially on March 3, 2014. As the panel data is gathered on January 1 of each year, the effect of recruiting before employment is captured in the data from year 2014, whereas the effect of employment is captured in the data starting from year 2015.

4.1.2 Closing of BB Sophia and Södra BB

On February 4, 2016, Praktikertjänst announced that BB Sophia would be closed the same year (Krey 2016). The clinic officially closed on May 31, 2016 (Praktikertjänst 2016). Proposals that Södra BB would be closed were submitted in the autumn of 2015, and the staff were moved to the adjoining hospital, Södersjukhuset during the spring, 2016 (Gustafsson 2015).

Similarly to above, since the data is gathered on January 1 of each year, the announcement of the closing of BB Sophia and the actual closing of BB Sophia and Södra BB are captured in the data from 2017, whereas the announcement of the closing of Södra BB is captured in the data from 2016.

4.1.3 Criteria for choosing treatment and control groups

Our study leverages that Sweden has well-defined nursing categories. Firstly, nurses require licenses issued by the Swedish National Board of Health and Welfare ("Socialstyrelsen"), which has complete coverage of all nurses that currently work or are eligible to work in the Swedish healthcare system. Furthermore, categories are uniquely identified by profession codes ("Kommunal befattningskod") issued by the Swedish Association of Local Authorities and Regions ("Sveriges Kommuner och Landsting, SKL").

Combined, this allows for using different nursing categories as treatment and control groups. While we hypothesize that midwives are suitably categorized as the treatment group, we used a two-pronged systematic approach to choose treatment and control groups where we independently investigated both qualitative data based on interviews and reports, as well as quantitative data of wage and employment developments in the time period of interest. The aim was to find concordant treatment and control groups, validated by both the qualitative and quantitative approach.

The ideal treatment group consists of nursing categories that have been employed by BB Sophia and Södra BB, but have otherwise had market conditions that have been analogous with the control group. Similarly, an ideal control group has had stable labor market conditions throughout the entire study period, alternatively been affected by labor market changes that affected both the control and the treatment group in a similar way.

In terms of qualitative data collection, we conducted interviews with key persons with knowledge of the labor market for nurses in Stockholm, such as senior members of the nurses' union, the Swedish Association of Health Professionals ("Vårdförbundet"), as well as the member association, the Swedish Association of Midwives ("Svenska Barnmorskeförbundet"), and the founder of BB Sophia. We also studied reports on nursing labor markets in Sweden by various governmental agencies and labor unions (Stockholm County Council 2013, 2014, 2016; Vårdförbundet 2016; Säther, Rabin Bozorg 2017).

Quantitatively, we conducted exploratory quantitative analysis using aggregate wage and employment data to identify nurse groups that have had stable employment and wage trends, as a characterization for stable labor market conditions. At this stage, we used both data of all public health providers in Stockholm, aggregate data from each hospital, as well as aggregate data from the National Board of Health and Welfare.

4.2 Econometrical Considerations

4.2.1 Random-Effects vs Fixed-Effects

While random-effects estimation is more efficient than fixed-effects estimation, it requires that regressors are uncorrelated with unobserved effects. Therefore, the Hausman-test was performed, the results supported the use of fixed-effects regression in favor of random-effects.

4.2.2 Heteroscedasticity

Based on preliminary analysis, heteroscedasticity is an issue and analyses will therefore use robust errors. In fixed-effects model, cluster-robust variance estimators are used as provided by STATAs xtreg package, with clustering at the individual level.

4.2.3 Attrition

Recently, Lechner et al. (2016) have raised the issue of attrition in fixed-effects difference-in-differences estimation using unbalanced panel data. One major issue is whether attrition affects the fundamental common-trend assumption. Lechner et al. demonstrate that such issues with attrition can be demonstrated by differences in OLS and FE estimation (Lechner, Rodriguez-Planas & Fernández Kranz 2016). As such, both FE and pooled OLS estimation will be used. Pooled OLS error terms were clustered at the level of clinics (over 130 clusters).

4.2.4 Serial correlation

Bertrand (2004) illustrated the potential issue of serial correlation in difference-in-differences estimation (Bertrand, Duflo & Mullainathan 2004). While several remedies are suggested, our study design is limited by the number of groups (in our case nursing categories). One of these solutions applicable in our case is to aggregate data into two periods: before and after.

4.2.5 Correlated earnings and selection on past outcomes

An issue notably brought to attention by Ashenfelter and Card (1985) is the issue of correlated earnings. As explained in their original article, the issue arises when salaries one year may depend on salaries the previous year, such as when there is a sudden shock that results in lower and higher wages, which would be corrected in the following period. However, based on preliminary analysis we deem that such shocks should affect our treatment and control groups equally. An example of this is that certain years are affected by two-year labor union contracts, as described in Section 5.3.2.. Nonetheless, we will use different pre-treatment time periods in our sensitivity analysis.

4.2.6 Statistics program

Statistical analyses were conducted using Stata 15.0.

4.3 Methodological Considerations

In this study, we have employed an econometrical approach to evaluate evidence for monopsony in nursing labor markets in Stockholm, Sweden. Certainly, other approaches such as theoretical and qualitative studies have an important role in the literature. For example, we diligently use theoretical models to explain why staffing nurses may be used to increase salary discrimination (Säther, Rabin Bozorg 2017).

However, we chose an econometrical route in part due to that it is in empirical evidence that there is substantial controversy in the field, as detailed in the background section. Arguably, well-executed econometrical studies provide among the highest levels of evidence within the frames given by theoretical models.

Many of the studies surveyed in our literature section, as well as our own, are constructed on the premise that reality as something that can be objectively assessed, and modeled. Many scholars believe that qualitative and quantitative approaches rely on different assumptions, and some researchers question the assumptions underlying quantitative research on the basis that it is deemed to always be limited (Atieno 2009). However, our ambition was to combine the strengths of qualitative and quantitative research. While quantitative assessments of economic models inevitability involve some simplification, a quantitative approach might be particularly appropriate when testing an already existing framework (Atieno 2009). We have devoted significant effort to preserve complexity of the issue and to critically review underlying assumptions of our model through interviews. Interviews were conducted mainly in search of facts that could be verified externally, wherefore we have not discussed the impacts of employed interview techniques, or the potential conflicts of interest.

5 Qualitative data: the nursing labor market in Stockholm

5.1 Swedish healthcare system

Here, we briefly introduce the structure of the Swedish healthcare system to provide some context for the rest of this study. Furthermore, we introduce important and relevant structural information that support our discussions of the results. Interested readers are advised to read the report by Stiernstedt et al. (2016), a recent comprehensive report on the Swedish healthcare system.

While there is universal healthcare in Sweden, healthcare in Sweden is not administered nationally, but by Sweden's 20 counties ("landsting" and/or "region"). Furthermore, non-medical care such as elderly care and social programs are administered by Sweden's 290 municipalities ("kommun"). Together, they form the Swedish Association of Local Authorities and Regions.

Importantly, the standards of healthcare are dictated by laws passed by the Swedish government and upheld by numerous governmental agencies organized under the Ministry of Health and Social Affairs ("Socialdepartementet"). A governmental agency of special interest for our study is the National Board of Health and Welfare, which administers licences for healthcare professionals, including nurses, and provides best-practice guidelines. Another important agency is the Swedish Agency for Health Technology Assessment and Assessment of Social Services ("Statens beredning för medicinsk och social utvärdering, SBU"), which evaluates and reports on the state of Swedish healthcare, including the report by Stiernstedt et al. mentioned above.

The Swedish healthcare system stands out internationally in several ways. Important to our study is that almost all healthcare is publicly financed, including private health providers such as BB Sophia. Private health providers are usually enumerated based on a capitation and/or fee-for-service model, depending on the kind of healthcare service provided.

5.2 Healthcare system in Stockholm

The healthcare system in Stockholm is administered by the Stockholm County Council. In central Stockholm there are two large emergency hospitals, Södersjukhuset, a public hospital, and S:t Görans sjukhus, the only private hospital. In close vicinity to the city of Stockholm are Karolinska University Hospital, which has one site in Solna (north of Stockholm), and one in Huddinge (south of Stockholm). Additionally, Danderyds sjukhus, located just north of Stockholm, is also included among the hospitals close to city.

There are two additional large emergency hospitals that are administered by the Stockholm County Council, Norrtälje sjukhus in the north, and Södertälje sjukhus in the south. However, we choose to define the labor market for nurses in Stockholm as employers more geographically centered than Norrtälje and Södertälje. This because commuting distance (and in translation, cost) is greater for locations further away.

5.2.1 Registered Nurses' and Specialist Nurses' education

To become a registered nurse in Sweden, one must complete a three-year nursing program at one of several nursing schools in Sweden. Usually after a couple years of work experience, nurses can then choose to specialize in one of 18 areas to become a specialist nurse. This specialist training is equivalent to one-year full time study but is most commonly done half-time in parallel with work over a two-year period.

Registered nurses are eligible to apply for specialist training to become a midwife after one-year of work experience. It is worth noting that midwife training is longer than other specializations, totaling 1.5 years of full-time study, usually pursued at full-time (Westlund 2018). Strictly speaking, midwives are not classified in the concept “specialist nurses” but are their own category. However, in this essay we refer them to as a type of specialized nurse, and therefore include midwives when we refer to specialist nurses.

5.2.2 BB Sophia

To identify nurses employed by BB Sophia, employment statistics were requested from the owners of BB Sophia, Praktikertjänst AB. Unfortunately, the request was denied. We identified through interviews that the by far largest specialist nursing category employed by BB Sophia were inpatient midwives, totaling 50–60 full-time midwives (Abascal 2018). Furthermore, midwife salaries at BB Sophia were targeted to be the same as those in the public sector. There was also a conscious effort to recruit a mix of junior and senior nurses. Other nursing categories included pediatric, anesthesiology, and surgical nurses. In the beginning of 2016, BB Sophia accounted for over 10% of births in Stockholm (Table 1).

Table 1. Births in Stockholm

Maternity Ward	Number of births per week (Jan-Apr, 2016) N / % of total	Number of births per week (Jan, 2018) N / % of total
Södersjukhuset	137 / 23.18%	152 / 27.01%
Södertälje sjukhus	32 / 5.41%	47 / 8.36%
Karolinska University Hospital in Solna	70 / 11.84%	75 / 13.32%
Karolinska University Hospital in Huddinge	84 / 14.21%	84 / 15.02%
Danderyds sjukhus	123 / 20.81%	126 / 22.51%
BB Stockholm	75 / 12.69%	77 / 13.77%
BB Sophia	70 / 11.84%	Closed

Source: Stockholm County Council (2016 and 2018).
Note that data on Södra BB is not included.

5.2.3 Södra BB

Södra BB was a combined maternity ward and outpatient clinic, that employed circa 50 midwives and was active from 1944 to its closing (Wikipedia 2017; Södersjukhuset 2012; Cullhed Engblom 2016). After its closing, midwives were offered employment by Södersjukhuset, while the clinic officially moved to Södertälje sjukhus along with reportedly seven midwives (Gustafsson 2016).

5.3 Labor market for nurses in Stockholm

5.3.1 Stockholm City Council Stimulus Package 2014–2015

Based on interviews and official documentation from Stockholm County Council, we identified a major salary compensation stimulus package for permanently employed specialist nurses employed by emergency hospitals in Stockholm during the years 2014–2015 (Stockholm County Council 2013). This stimulus package consisted of an additional 59 million SEK per annum aimed at increasing salary of senior and high-performing specialist nurses (as well as biomedical analysts), as an explicit effort to increase salary discrimination. The nursing categories affected by this stimulus package were nurses specialized in surgery, intensive care, pediatrics, oncology, anesthesiology and inpatient midwives (Stockholm County Council 2014). The stimulus package stipulated a minimum salary increase of 1,500 SEK monthly per selected nurse, whom were distinguished and "added value" to the workplace. However, the selection criteria were open for interpretation. In practice, management at the clinic-level oversaw selection of receiving nurses (Allerstam 2018.). As far as we know, there have been no detailed reports on the effects of the stimulus package, apart from a short report that saw an increase in the standard deviation and median salary for affected nursing categories (Stockholm County Council 2016; Allerstam 2018.). In the context of our study, it is important identify treatment and control groups that are (un)affected by the stimulus package in a similar way.

5.3.2 Labor Union Contracts for Nurses

Labor union contracts ("kollektivavtal") regulate many aspects of employment, also for non-union members. The labor union contract that affects nurses are negotiated by the Swedish Association of Health Professionals. Several details were identified in the qualitative data that are important for our quantitative analysis.

Firstly, salaries for permanent employees are renegotiated on April 1 of every year. However, new hires may have other start-dates, commonly January 1. As our data is based on payroll information on January 1, we essentially capture the salaries settled in negotiations for the previous year for permanently employed nurses.

Secondly, some labor union contracts may be stipulated in 2-year periods. Reportedly, the 2011 labor union contract at Karolinska University Hospital stipulated for wage increases for the period 2011–2012 (captured in our data by 2012–2013), to be fully encompassed during the first year (Allerstam 2018.).

6 Dataset and summary statistics

6.1.1 Panel data for all nurses in public sector in Stockholm

Our primary dataset used for the main analyses is a panel dataset based on administrative payroll data for all nurses employed by the public sector in Stockholm County from 2010 to 2018 provided by the Stockholm County Council. The data is based on the status of nurses on January 1 of every year.

In more detail, the data contains demographic variables including gender and age; detailed employment data including title and profession, working hours, monthly salary, cash bonuses, whether they work full time or part time (as a percentage of a full-time contract); employment contract information such as whether they are permanently or temporarily employed, and whether it is their first time being employed at a given hospital/clinic. A full set of variables are contained in Appendix 1.

Our dataset does not include staffing nurses and non-recurring compensation. Examples of non-recurring compensation are bonuses offered during the summer and overtime compensation.

6.1.2 Hospital-level aggregated data

Aggregate employment and salary data for each nursing category were obtained from the three public emergency hospitals in Stockholm: Danderyd Hospital, Södersjukhuset, and Karolinska University Hospital, provided by the human resource department of each hospital. This data was used primarily for validation of the main panel dataset.

6.1.3 Aggregate data from the National Board of Health and Welfare

Aggregate employment and salary data for some nursing categories were obtained from the National Board of Health and Welfare, stratified by nursing category, profession, number of nurses employed in public alternatively private sector, number of nurses employed in and outside the healthcare sector, grouped at the county level.

6.2 Descriptive quantitative data

In total, our primary dataset had 122,940 observations including all nurses and specialist nurses, as well as other non-physician personnel employed by Stockholm County Council and its subsidiary companies during 2010-2018, based on administrative payroll data on January 1 of every year. Of these, non-nurses, employees at Norrtälje and Södertälje hospitals, as well as nurses with managerial or administrative duties were excluded (24,071 obs). Furthermore, exact duplicates (13 obs), entries registered to non-existing workplaces (1,152 obs) were excluded. Nursing categories with less than 100 observations during the entire study period were also excluded (106 obs). Our final study sample contained 97,598 observations, which was further grouped into 14 nursing categories: ambulance, inpatient midwives, outpatient midwives, district, registered nurses (without specialization), intensive care (ICU), anesthesiology, pediatrics, geriatrics, oncology, surgical (OR), psychiatry, radiology and ophtamology (summary statistics per group are included in Appendix 2). The grouping between inpatient and outpatient midwives were provided by Stockholm County Council, however midwives that were coded as inpatient midwives but worked at outpatient clinics were recoded manually to outpatient midwives.

Summary statistics for the cohort is presented in Table 2, stratified by time period before BB Sophia opened (2010–2014), when BB Sophia was open (2015–2016), and after the closing of Sophia BB and Södra BB (2017–2018). The number of total employees per year was stable at around 10,600. The average number of registered nurses per year during the study period is 5,999, compared to 4,845 for specialist nurses. Both categories remain relatively stable, although both groups increase from 2010–2014 to 2015–2016, and decrease from 2015–2016 to 2017–2018. On average, 90% of all nurses are females. The median age for registered nurses is 39 (standard deviation 11.1) years and 49 (10.4) years for specialist nurses.

Median salaries and standard deviations are increasing over time for both registered nurses and specialist nurses. Registered nurses' median salary is 26,000 (3,644) in 2010–2014 and 31,000 (4,232) in 2017–2018. Specialist nurses' median salary is 30,400 (3,584) in 2010–2014, and 35,750 (4,282) in 2017–2018. Median bonuses are similar between registered nurses and specialist nurses in magnitude, although the growth is somewhat more pronounced for registered nurses than specialist nurses.

Table 2. Descriptive population statistics

	Time Period			
	2010–2014	2015–2016	2017–2018	Entire study period
1. Number of observations / Number of observations per year	54,250 / 10,850	21,957 / 10,979	21,391 / 10,696	97,598 / 10,844
1a. Registered Nurses, mean per year	6001	6069	5925	5999
1b. Specialist Nurses, mean per year	4849	4910	4771	4845
2. Proportion of females	0.90	0.90	0.89	0.90
3a. Median age (S.D.) - Registered Nurses	39 (10.9)	39 (11.2)	39 (11.5)	39 (11.1)
3b. Median age (S.D.) -Specialist Nurses	49 (10.1)	49 (10.6)	48 (10.9)	49 (10.4)
4a. Median salary incl. bonus (S.D) - Registered Nurses	26,000 (3,644)	29,100 (3,774)	31,000 (4,232)	27,850 (4,340)
4b. Median salary incl. bonus (S.D) - Specialist Nurses	30,400 (3,584)	34,000 (4,163)	35,750 (4,282)	32,300 (4,542)
5a. Mean bonus (S.D) , Registered Nurses**	1953 (874)	2481 (1241)	2853 (1376)	2328 (1193)
5b. Mean bonus (S.D), Specialist Nurses**	1931 (912)	2265 (1027)	2489 (1063)	2168 (1014)
6. Proportion of nurses receiving bonuses	0.09	0.12	0.15	0.11
7. Proportion of nurses working full-time	0.83	0.85	0.85	0.84
8. Proportion of nurses working office hours	0.34	0.37	0.38	0.35
9. Proportion of nurses permanently employed	0.79	0.79	0.77	0.79
10. Annual salary growth, aggregate mean***	2.3%	3.5%	3.1%	2.8%

*Nurses refer to all nursing categories unless specified.
** Of those that receive bonuses
*** Annual mean of the growth rate of median salary

Standard deviation for bonus increase over time for both groups, and so does the proportion of nurses that receive bonuses: from 9% in 2010–2014 to 15% in 2017–2018.

The proportion of nurses working full-time and proportion of nurses that are permanently employed are stable at around 84% and 79%, respectively, with a decrease in the last period. The proportion of nurses working normal office hours appears to be rising, from 34% in 2010–2014, 37% in 2015–2016, and 38% in 2017–2018 – averaging at 35% over the study period. The annual salary growth rate is computed as the mean growth of the median salary for the whole sample. This growth is 2.3% in 2010–2014, 3.5% in 2015–2016, and 3.1% in 2017–2018. Thus, the average annual growth of the median salary is 2.8% over the study period.

7 Results

7.1 Treatment and control groups

Based on qualitative and preliminary quantitative data, we identified pediatric, surgical, anesthesiology and inpatient midwives as nursing categories employed by BB Sophia. The major nursing group were inpatient midwives and were therefore selected as the primary treatment group.

Out of nursing categories affected by the 2014–2015 stimulus package, only intensive care and oncology nurses were not employed by BB Sophia. However, oncology nurses are relatively few and have large fluctuations in employment levels. As such, intensive care nurses were therefore selected as the primary control group.

7.2 Descriptive data based on treatment and control groupings

Table 3 presents descriptive statistics stratified by selected groupings of nursing categories, and time periods of interest. Non-affected nurses is the largest group by far, with around 8,000 employees, whereas intensive care nurses is the smallest. The number of nurses was on average highest during 2015–2016 for all groups except inpatient midwives. The proportion of junior nurses with 0–5 as well as 6–10 years of potential experience (calculated by age and length of education) has increased during the study period for all groups, whereas the proportion of the most experienced group (16+ years of potential experience) has decreased for inpatient midwives, non-affected nurses, whereas it has increased for intensive care nurses and remained the same for other affected nurses.

Median salary is characterized as both the mean median salary for the study period, but also as the mean growth of the median salary per year, and is discussed in more detail below.

Employment levels refer to the proportion of number of hours that a nurse is scheduled to work divided by the number of hours that a full-time employee would work given the same working hours.[5] Employment levels are relatively stable for all groups. They have risen modestly, and constantly, for inpatient midwives and non-affected nurses, meaning that their employment levels peaked in 2017–2018. For intensive care nurses and other affected nurses, the peak in employment levels was in 2015–2016. Inpatient midwives have the lowest employment levels of all groups, between 87.3–89.2%. Intensive care nurses have the highest employment levels, between 97.9–98.0%.

[5] For example, a nurse that works primarily night-shifts works 1940 hours per year; if they work 1552 hours per year, their employment level is 1552/1940=0.8.

Table 3. Descriptive statistics categorized by groups of interest

	Nursing categories (2010–2014 2015–2016 2017–2018)*											
	Inpatient Midwives			Intensive Care (ICU)			Other affected nurses**			All non-affected nurses***		
1. Number of nurses, per year (%)	846 (100%)	826 (100%)	830 (100%)	618 (100%)	623 (100%)	586 (100%)	1443 (100%)	1493 (100%)	1475 (100%)	7943 (100%)	8038 (100%)	7806 (100%)
1a. 0–5 years potential experience (%)	23 (3%)	25 (3%)	45 (5%)	31 (5%)	37 (6%)	37 (6%)	45 (3%)	60 (4%)	85 (6%)	991 (12%)	1029 (13%)	1182 (15%)
1b. 6–10 years potential experience (%)	124 (15%)	112 (14%)	130 (16%)	106 (17%)	100 (16%)	105 (18%)	207 (14%)	204 (14%)	232 (16%)	1535 (19%)	1647 (20%)	1590 (20%)
1c. 11–15 years potential experience (%)	160 (19%)	145 (17%)	142 (17%)	131 (21%)	108 (17%)	91 (16%)	308 (21%)	286 (19%)	259 (18%)	1318 (17%)	1208 (15%)	1155 (15%)
1d. 16+ years potential experience (%)	538 (64%)	544 (66%)	513 (62%)	349 (57%)	379 (61%)	354 (60%)	882 (61%)	943 (63%)	899 (61%)	4099 (52%)	4155 (52%)	3880 (50%)
2. Median salary including bonus (S.D)	31,350 (4,019)	35,878 (4,311)	36,850 (4,641)	31,400 (3,686)	36,100 (4,331)	37,800 (4,495)	30,500 (3,390)	34,600 (4,046)	36,500 (4,145)	27,210 (3,844)	30,200 (3,954)	32,000 (4,318)
3. Annual salary growth of median salary, mean	2.8%	4.0%	1.8%	2.7%	4.3%	2.9%	2.9%	3.5%	3.1%	2.2%	3.6%	3.2%
3. Proportion that receive bonus	0,07	0,08	0,10	0,17	0,19	0,29	0,10	0,11	0,16	0,09	0,12	0,14
4. Mean bonus (S.D.) among bonus receivers	1558 (916)	2018 (891)	2530 (1330)	2256 (871)	2466 (928)	2570 (968)	2040 (789)	2458 (1081)	2592 (1041)	1906 (895)	2404 (1217)	2675 (1336)
5. Employment level	87.3%	88.5%	89.2%	97.9%	98.4%	98.0%	95.6%	96.3%	96.0%	96.8%	97.1%	97.3%
6. Proportion working full-time	0,47	0,50	0,52	0,91	0,93	0,93	0,83	0,86	0,85	0,86	0,87	0,88
7. Proportion permanently employed	0,80	0,83	0,83	0,77	0,73	0,71	0,82	0,80	0,79	0,79	0,78	0,77
8. Proportion working normal office hours	0,15	0,18	0,17	0,06	0,07	0,08	0,48	0,49	0,47	0,35	0,39	0,41
9. Median age (S.D)	48 (9.9)	49 (10.5)	47 (10.9)	45 (9.3)	47 (10.1)	47 (10.5)	47 (9.9)	47 (10.2)	47 (10.4)	43 (11.5)	43 (11.8)	42 (12.0)
10. Median age (S.D) of new hires	39 (8.7)	41 (9.9)	41 (11.0)	40 (9.3)	41 (10.3)	50 (10.7)	41 (9.3)	43 (8.9)	44 (9.6)	33 (9.7)	34 (10.2)	34 (10.7)
11. Median age (S.D) of nurses that quit	45 (11.2)	49 (11.9)	47 (11.0)	43 (9.8)	47 (10.9)	48 (11.1)	44 (10.9)	46 (11.2)	46 (11.1)	38 (12.1)	40 (12.4)	39 (12.4)

*Column percentages may not sum up to exactly 100% due to rounding.
** Affected nurses include nurses specialized in pediatrics, surgery, and anesthesiology.
*** Non-affected nurses include all other nursing categories including registered nurses.

The proportion of nurses working full-time has risen constantly during the study period for inpatient midwives, intensive care nurses and non-affected nurses. For other affected nurses on the other hand, the proportion working full-time peaked in 2015–2016. The proportion working full-time is lowest among inpatient midwives and highest among intensive care nurses (47–52% and 91–93% respectively).

The proportions of staff working normal office hours, defined as those contracted to work 2400 hours a year, is lowest for intensive care nurses and inpatient midwives (6% in 2010–2014 and 15% in 2010–2014 respectively) and rise slowly during the period of study. This number is 48% for other affected nurses in 2010–2014, and it remains relatively stable during study period. A more dramatic change is seen for non-affected nurses, going from 35% of nurses working office hours in 2010–2014 to 41% in 2017–2018.

Median age is stable for all four groups over the study period, with some fluctuations with at most 1–2 years. However, standard deviation is consistently increasing, suggesting increased age dispersion.

Age of new hires and nurses that quit are calculated based on if they were in the dataset the previous year or the following year, respectively. As such, 2010 and 2018 are excluded from this calculation. Median age of new hires is consistently lower than the median age of those that quit, except for intensive care nurses during 2015–2016 and 2017–2018.

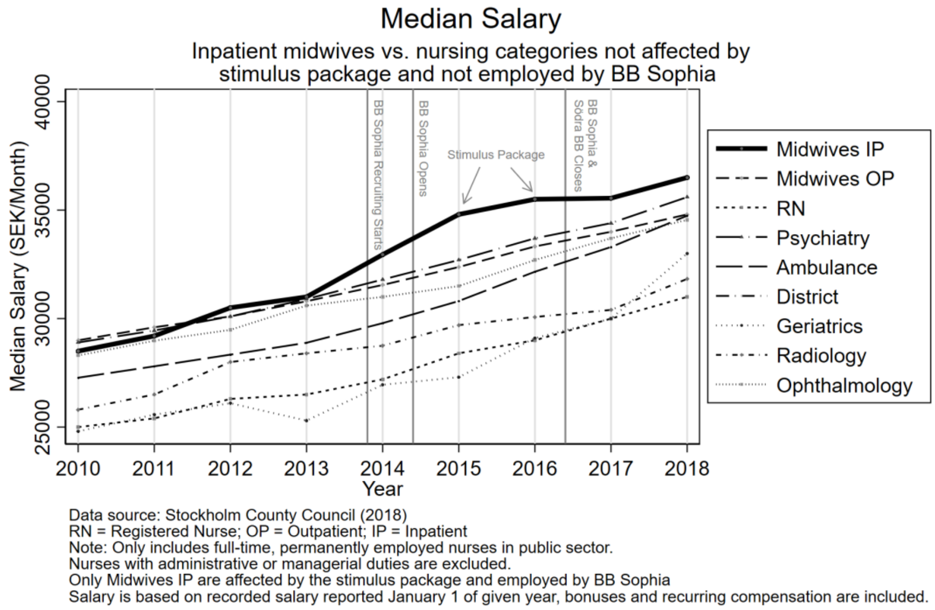

Fig 4. Median salary for inpatient midwives compared to nursing categories not affected by the stimulus package nor employed by BB Sophia.

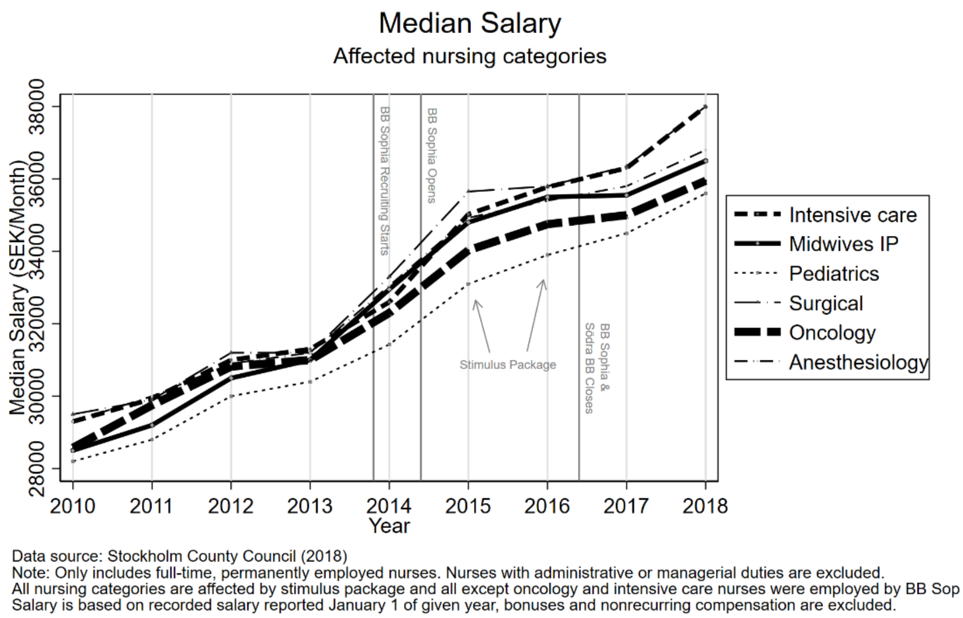

Fig 5. Median salary for nursing categories included in stimulus package.

Figure 4 and 5 compare inpatient midwife salary trends to affected and non-affected groups. Figure 4 describes inpatient midwives' median salary development compared to nursing categories unaffected by BB Sophia, Södra BB and the stimulus package. Nursing categories neither affected by the stimulus package nor employed by BB Sophia had a steady median salary increase per annum during the study period (Figure 4). Inpatient midwives, on the other hand, affected both by the stimulus package and employed by BB Sophia experience a noticeable wage increase during 2015–2016. No midwives changed between inpatient and outpatient contracts throughout the study period within the dataset (data not shown).

Figure 5 compares median salaries for all nursing categories affected by the stimulus package, including the subset of nurses also employed by BB Sophia (all except intensive care and oncology nurses).

Salary trends are reasonably parallel for all nursing categories prior to 2014, in both Figure 4 and 5. The nursing categories in Figure 5 experience significant median salary growth in years 2014–2015 compared to nurses not affected by the stimulus package or employed by BB Sophia or Södra BB in Figure 4. Inpatient midwives and oncology nurses have somewhat flatter salary development between 2016–2017, compared to all other nursing categories, whereas all nursing categories have relatively parallel salary developments 2017–2018.

Lastly, Figure 6 isolates median salary trends for our primary treatment and control group, inpatient midwives and intensive care nurses, respectively. Salary trends prior to 2014 are reasonably parallel, whereas median salaries for intensive care nurses converge and eventually overtakes median salaries for inpatient midwives on an aggregate level. It is important to note, however, that the proportion of senior nurses increase for intensive care nurses, whereas they decrease for inpatient midwives, as discussed above.

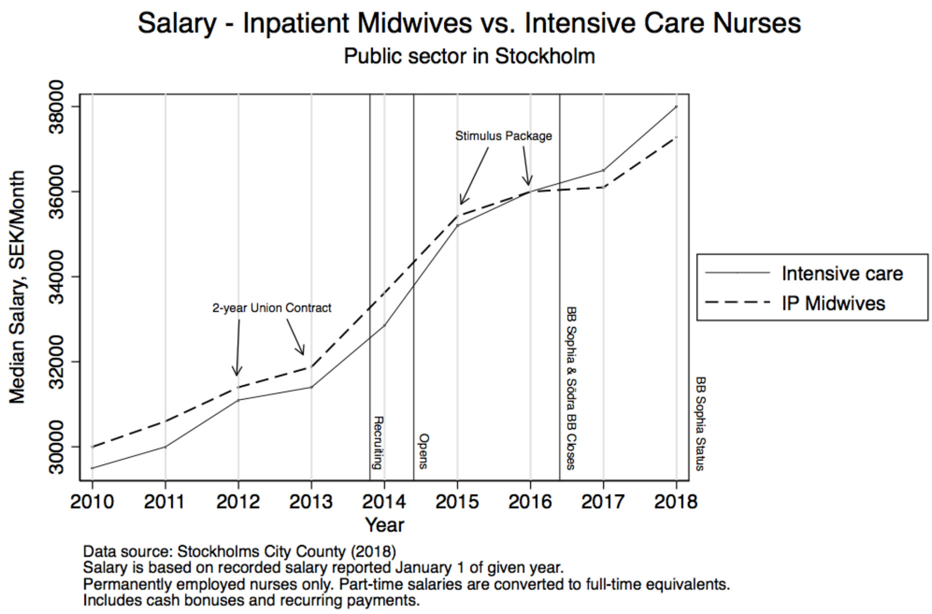

Fig 6. Median salary - inpatient midwives versus intensive care nurses

7.3 Difference-in-differences estimation of effect on salary

Results from difference-in-differences using both pooled OLS and FE regressions on log-transformed salary is displayed in Table 4. The base specifications for the opening of BB Sophia, and the closing of BB Sophia and Södra BB are shown in specification 1 and 6, respectively. The final specification using primary treatment and control groups, with controls for various time-dependent covariates, are specified in specification 3 and 8, respectively. Secondary analyses use variations of treatment and control groups, which are in specification 4 and 5, as well as 9 and 10, respectively.

The final fixed-effects specification for the opening of BB Sophia (specification 3) used 5887 observations and showed a circa 0.00345 ($p<0.01$) difference in log salary, corresponding to circa 0.35% difference in salary development, in favor of inpatient midwives

Table 4. Difference-in-differences estimates on log(salary)

Opening of BB Sophia (2013–2014 vs 2015–2016)	Fixed effects	Pooled OLS	N
Primary analysis - Inpatient midwives (treatment) versus ICU nurses (control)			
1. Base specification	0.00349** (2.92)	0.00244 (0.83)	5887
2. Control for age category, employment type, and working hours	0.00387*** (3.50)	0.00260 (1.07)	5887
3. Control for year effects	0.00345** (3.19)	0.00265 (1.12)	5887
Secondary analysis			
4. Inpatient midwives vs. ICU nurses + Oncology nurses (secondary control)	0.00565*** (5.56)	0.00492* (2.29)	6637
5. All affected nurses (secondary treatment) vs. ICU nurses + Oncology nurses (secondary control)	0.00271*** (3.34)	0.00212 (1.24)	12575
Closing of BB Sophia and Södra BB (2015–2016 vs 2017–2018)			
Primary analysis - Inpatient midwives (treatment) versus ICU nurses (control)			
6. Base Specification	-0.00411*** (-4.22)	-0.00958** (-3.16)	5727
7. Control for age category, employment type, and working hours	-0.00358*** (-3.96)	-0.00725** (-3.16)	5727
8. Control for year effects	-0.00379*** (-4.42)	-0.00745** (-3.24)	5727
Secondary analysis			
9. Inpatient midwives vs. ICU nurses + Oncology nurses (secondary control)	-0.00243** (-3.18)	-0.00623** (-2.64)	6513
10. All affected nurses (secondary treatment) vs. ICU nurses + Oncology nurses (secondary control)	-0.00100 (-1.41)	-0.00163 (-0.77)	12447

t-statistics in parenthesis; * p<0.05, ** p<0.01, *** p<0.001

Includes full time and part-time employees, where part-time salaries have been converted to full-time equivalents.
Includes permanent as well as temporary contracts. Bonuses and recurring compensation is included.

compared to intensive care nurses. Secondary specifications showed larger differences with intensive care nurses and oncology nurses, weighted by number of employees, as control (0.00565, $p<0.001$), whereas smaller differences when all specialist nursing categories employed by BB Sophia were used as the treatment group (0.0271, $p<0.001$)

As for the closing of BB Sophia and Södra BB, fixed-effect estimates showed a -0.0379 ($p<0.001$) difference in log salary, this time in favor for intensive care nurses. Secondary specifications showed less difference between treatment and control groups, and the null hypothesis could not be rejected at the 0.05 level when all specialist nursing categories employed by BB Sophia were compared to intensive care nurses and oncology nurses as control.

Pooled OLS estimates could not reject null hypothesis for specifications for the opening of BB Sophia, and were more negative for the closing of the maternity wards. Interpretations on why OLS results may differ from fixed-effect estimates are discussed in section 8.

7.4 Employment

Figure 7 compares the employment of publicly employed intensive care nurses and inpatient midwives, measured by the number full time equivalents. Trends are generally parallel, although employment in intensive care nurses continuously decline after 2014, whereas there is a rebound for inpatient midwives in 2017.

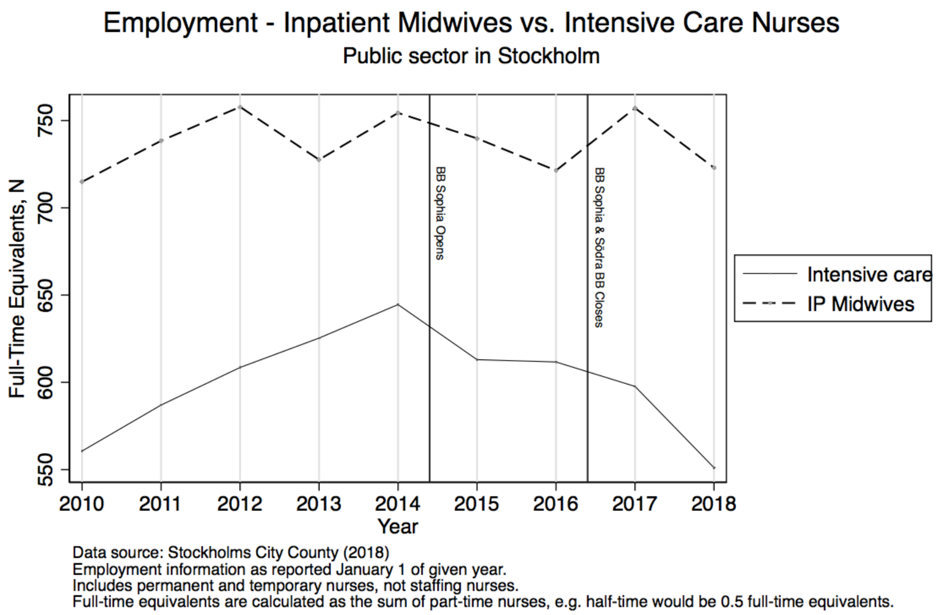

Fig 7. Employment – Inpatient midwives versus intensive care nurses

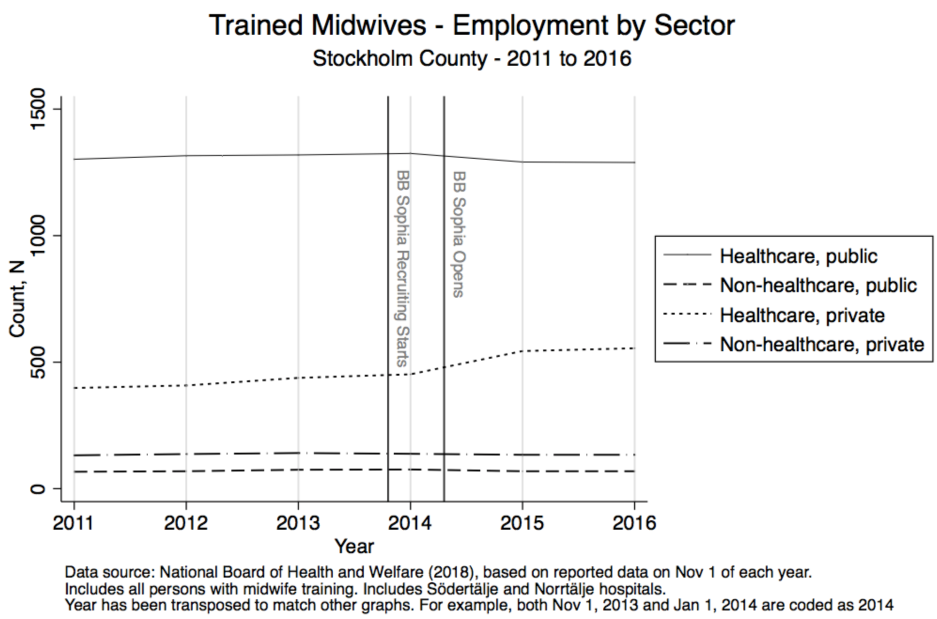

Fig 8. Number of midwives in Stockholm County

Figure 8 presents publicly available data from the National Board of Health and Welfare on employment for individuals with a midwife license (that can work as both inpatient and outpatient midwives) in Stockholm County. These are stratified by public/private sector, as well as whether they are employed within/outside of the healthcare sector. The distribution and number of individuals in each category is generally stable up to 2014. In 2015, in conjunction with the opening of BB Sophia, the number of individuals employed in the private healthcare sector increases, while it decreases in the public healthcare sector. The average employment level (all nurses in healthcare) increased about 1.5% per year before 2014, and rose with 3.3% in 2015. Levels in non-healthcare sectors are stable. Unfortunately, data for more recent years has yet to be published, and intensive care nurses are not reported as a discrete group in publicly available data.

8 Discussion

8.1 Sensitivity analysis

Results from sensitivity analyses are presented in Table 5. The first section deals with sensitivity analyses of the difference-in-differences estimation on effects of the opening of BB Sophia. The first specification (1) tackles the main assumption in difference-in-differences estimation: the identification assumption. In short, this assumes that without the treatment effect, the treatment group (inpatient midwives) would otherwise have the same salary development as the control group (intensive care nurses). While salaries for the two groups seem parallel in graphical representations (Figure 8), this was also tested using non-treatment years (2013 – 2014) as the treatment years in this sensitivity analysis. Indeed, the null hypothesis cannot be rejected at

Table 5. Robustness analysis

Opening of BB Sophia (2013–2014 vs 2014–2016)	Difference-in-Differences	t statistic	N
1. Fixed effects (3) but different time period (2011–2012 vs 2013–2014)	-0.000617	(-0.85)	5924
2. Fixed effects (3) but instead Outpatient midwives versus ICU	-0.0180***	(-15.74)	3289
3. Fixed effects (3) but Inpatient midwives versus Pediatrics, OR, and Anesthesiology nurses	0.00459***	(4.90)	9287
4. Fixed effects (3) but extend back to 2012	0.00366**	(3.17)	7372
5. Fixed effects (3) but remove Karolinska University Hospital	0.00444**	(2.60)	2728
6. Fixed effects (3) but remove Danderyd Hospital	0.00405***	(3.56)	4845
7. Fixed effects (3) but 2014 coded as anticipation†	-0.000476	(-0.52)	7372
8. Fixed effects (3) with Ophtamology nurses versus Psychiatry nurses	0.00456	(1.84)	2133
9. Fixed effects (3) with Outpatient midwives versus Psychiatry nurses	0.000561	(0.56)	2651
Closing of BB Sophia and Södra BB (2015–2016 vs 2017–2018)			
10. Fixed effects (9) but Inpatient midwives versus Pediatrics, OR, and Anesthesiology nurses	-0.00251***	(-4.39)	9277
11. Fixed effects (9) with Ophtamology nurses versus Psychiatry nurses	0.00356*	(2.32)	1981
12. Fixed effects (9) with Outpatient midwives versus Psychiatry nurses	0.00000897	(0.01)	2526

†Coefficient is for 2014 difference-in-difference term

* p<0.05, ** p<0.01, *** p<0.001

Includes full time and part-time employees, where part-time salaries have been converted to full-time equivalents.
Includes permanent as well as temporary contracts, bonuses and recurring compensation is included.

the α =0.05 level, and estimates are close to zero (-.000617), in support of the parallel trends assumption.

In the second specification (2), outpatient midwives are used as a treatment group compared to intensive care nurses as control, to see if the effect of the stimulus package can be observed, as a positive control. Since outpatient midwives were not employed by BB Sophia nor subject to the stimulus package that targeted intensive care nurses and inpatient midwives, the coefficient -0.0180 significant at the α = 0.001 level, is in line with expectations.

The third specification (3) uses inpatient midwives as the treatment group, and all other nursing categories affected by the opening of BB Sophia *and* the stimulus package, as the control group. In this specification, both treatment and control group have been subject to similar labor market changes. If the nursing categories were affected in a similar fashion, we should expect a zero coefficient. The estimate of 0.00459 is significant at the α = 0.001 level, perhaps indicating that inpatient midwives were more affected by the maternity ward's opening than other employed nursing categories. This finding is also in support of the results in (5) of our main regressions in Table 4, i.e. that the observed treatment effect is less when these nursing groups are used as the treatment group in aggregate.

The fourth specification (4) extends the panel back to 2012, with inpatient midwives as treatment group, and intensive care nurses as control. While selection on past outcomes, as discussed in the methods section above, may pose an issue in difference-in-differences estimation, we argue that this is not a major issue in our case as we expect our control group to have been affected in the same way as our treatment group. To test whether different pre-treatment years could affect our estimates, especially 2012 which was the first year of the 2-year labor union contract, the pre-treatment years were extended to include 2012. Indeed, no substantial differences were observed, supporting the interpretation that selection on past outcomes is not a major issue in our estimation model.

As the two-year labor union contract reportedly mostly affected Karolinska University Hospital, resulting in higher than normal salaries in 2012 and lower than expected 2013 salary growth, exclusion of Karolinska University Hospital was used as an alternative sensitivity analysis in specification 5. No large differences were observed compared to the original regression, although it is at a lower significance level to be expected from a smaller sample size. Again, this suggests that correlated earnings is not an issue.

One of our interviews identified Danderyd Hospital as explicitly offering higher wages to inpatient midwives in reaction to BB Sophia. Therefore, Specification 6 excluded Danderyd Hospital to test whether this was an isolated incident that drove estimates upwards in our main results. Even with the exclusion of Danderyd Hospital, similar effects can still be observed (0.00405), significant at the $\alpha = 0.001$ level, indicating that the treatment effect was not isolated to Danderyd Hospital.

As recruiting (but not hiring) at BB Sophia started already in late 2013, anticipatory effects may be seen in already on January 1, 2014, which may lead to smaller differences between pre-treatment and treatment years and therefore underestimate the treatment effect. As such, Specification 7 tests whether salaries diverged between control and treatment groups already in 2014 in anticipation of BB Sophia. No such effects could be observed.

As a negative control, salaries between nurses specialized in ophthalmology and psychiatry were compared (Specification 8). Although no in-depth qualitative data were collected on these two specific nursing categories, their labor market is reasonably assumed to be unrelated to maternity wards. No difference can be observed in this negative control.

Finally, to explore whether outpatient midwives were also affected by the opening of BB Sophia, we compared them to psychiatric nurses in a ninth specification (9). Since outpatient midwives are eligible to work as inpatient midwives as well, we may expect them to be affected by the opening of BB Sophia, as working opportunities increase. Both nursing categories were excluded from the stimulation package. Our estimate is close to zero and statistically insignificant, suggesting that there might be no or small effects.

The second section deals with sensitivity analyses of the difference-in-differences estimation on effects of the closing of BB Sophia and Södra BB. Indeed, interpretation of this second difference-in-differences estimation is more problematic due to numerous reasons. Firstly, lowering wages is problematic, especially due to labor union contracts. As such, effects may manifest in different ways, such as primarily affecting entry wage. While we originally set out to analyze entry wages, the number of new hires is small and hiring new junior nurses is even less common. Combined with the limited number of years of data, it is therefore difficult to estimate entry wages. Furthermore, the parallel trends assumption may be violated, as we have in the estimate of the effects of BB Sophia opening essentially shown a significant difference between our treatment and control groups during 2015–2016, our pre-treatment years for the second difference-in-differences estimation. Indeed, an ideal control group would have continued to be employed by BB Sophia whereas the treatment group was not. Although the difference is small, for all the reasons mentioned above, it is our understanding that the results from the first difference-in-differences estimation may be more informative.

Still, to gauge sensitivity in this second analysis, inpatient midwives were compared to other nursing categories employed by BB Sophia in Specification 10. As inpatient midwives may be expected to be more affected by the closing of BB Sophia, we may see that their salaries are more negatively impacted compared to other nursing categories also employed by BB Sophia. Indeed, results from our sensitivity analyses supports this claim.

Furthermore, a negative control in Specification 11 compared again nurses specialized in ophthalmology and psychiatry. Some difference was observed, although only at the $\alpha = 0.05$ level. We interpret this as essentially an affirmative negative control, due to the low statistical significance and the large number of sensitivity regressions.

Finally, outpatient midwives were compared to psychiatric nurses in the closing treatment as well, analogous to Specification 9. The estimate is very close to zero and not statistically significant, suggesting that outpatient midwives were not affected by the closing of maternity wards. Together with (9), we interpret that outpatient midwives were not affected by the possibility of working at BB Sophia, or the observed effect on inpatient midwives is not driven by BB Sophia but by other unobserved factors. This is discussed more in the next section.

8.2 Difference-in-differences assumptions

The first assumption for a difference-in-differences approach to be viable, is that of independent sampling (Callaway, Sant'Anna 2018) However, we are looking to only estimate salary effects among those that remain in the public sector, and as such we have complete coverage of the entire population.

The second assumption is conditional parallel trends (Callaway, Sant'Anna 2018). While both our exploratory and sensitivity analyses support that there are parallel trends before the opening of BB Sophia, the coinciding stimulus package may challenge parallel trends during the study period, as explored in detail above. Furthermore, the observed differences for the opening of BB Sophia essentially argues against parallel trends prior to the closing of BB Sophia, as we use the same treatment and control groups for estimating effects of the closing of the maternity wards. However, the differences are very small.

The third and fourth assumptions, irreversibility of treatment and overlap between treatment and control groups, are both deemed to be met in for the primary treatment and control groups (Callaway, Sant'Anna 2018). We observed no overlap using person-specific IDs in the dataset during the entire study period, and no midwives switched groups during the study period. Furthermore, specialist nursing training takes a number of years, which creates a significant threshold for overlap during a study period of 2–4 years.

8.3 A monopsony in the nursing labor market in Stockholm?

At a glance, the case could be made that the Stockholm nursing market is ideal for classical monopsony. There are a handful of large employers, almost all owned and financed by the Stockholm County Council. There is a pressing nursing shortage, with frequent reports on newly graduated nurses abstaining work that offer under a certain salary or more senior nurses that quit in protest, often due to salary disputes. Furthermore, media as well as labor unions frequently emphasize the narrow spread in wages amongst nurses, which could be interpreted to be a sign of low wage discrimination.

Below, we discuss our results on salary and employment separately, and finally synthesize our findings and compare them with previous literature.

8.3.1 Salary

The signs of our difference-in-difference estimates are consistent with the hypothesis that salaries of inpatient midwives, which are assumedly most affected by the opening and closing of maternity wards, where positively affected by the opening BB Sophia and negatively when the maternity wards closed.

The magnitudes of the estimates, while statistically significant, are small. In fact, our results suggest that the relative difference in salary for inpatient midwives compared to the control is around 0.3%, and -0.4%, after the opening and closing of the maternity wards, respectively. Furthermore, the effects are smaller when secondary treatment groups are used, which is in line with our expectation that nursing categories employed to a lower extent by maternity wards would be less affected. This is also supported by our sensitivity analyses comparing inpatient midwives to other nursing categories employed by BB Sophia. As previously discussed, the first estimation model that evaluates the opening of BB Sophia is likely more informative, due to stronger support for parallel trends, better control group, as well as lack of data for entry wages.

Interestingly, pooled OLS estimates were consistently lower than fixed-effect estimates, i.e. no difference in the opening of BB Sophia, and an even higher penalty to salary development for inpatient midwives after the closing of the maternity wards. If attrition were indeed an issue, we would expect that BB Sophia hired more senior nurses (although this was rejected in interviews), and as such pooled OLS estimate may be expected to be lower than fixed-effect estimates for the opening of BB Sophia.

However, if issues due to attrition was driving these differences, we would expect the opposite direction for pooled OLS estimates for the closing of BB Sophia as more experienced nurses would return, which is the opposite of our results. Instead, the difference between fixed-effects regression and pooled-OLS is more likely driven by the gradual increase in the proportion of more senior nurses in intensive care nurses (the control), which may not be adequately controlled by age groups, but better controlled for in combination with individual fixed-effects. As such, the OLS estimates do not readily support that attrition biases the fixed-effects estimates. Furthermore, our model predicts that even salaries among the nurses that stay in the public sector should increase from decreased employer concentration, whereas comparisons of OLS and fixed-effects estimates were aimed at generalizing trends to both publicly and privately employed nurses. As such, deviations between OLS and fixed-effects estimates do not readily affect our interpretation, and we will hereon discuss only the fixed-effect estimates which are more relevant for our research question. The case could be made that the results are in support for classical monopsony, in the sense that there is an observable effect in the predicted direction. In this context, numerous reasons could explain why the magnitude is small. Firstly, only 50–60 inpatient midwives were reportedly employed by BB Sophia, out of over 1000 midwives in Stockholm. By extension, the resulting difference in employer concentration is rather small. During interviews, we also identified numerous mechanisms used by employers to increase wage dispersion. The 2014–2015 stimulus package, in itself, was aimed at increasing wage dispersion. Previous studies have examined how staffing nurses in Sweden allow employers to essentially wage discriminate (Säther, Rabin Bozorg 2017). Furthermore, there is anecdotal evidence that employers used different forms of one-time or non-regular bonuses to retain nurses (Allerstam 2018.). As our dataset does not contain information on staffing nurses, or non-regular bonuses, we are unable to take these into consideration. As such, we are unable to observe shifts to using more expensive staffing nurses as an alternative manifestation of increased salaries. However, all the mechanisms listed above can be examined as methods that increase wage dispersion, and therefore reduce the marginal factor cost of labor. In the classical monopsony model, this in turn would lower the positive effect on wages in the scenario of decreased market concentration.

Furthermore, the treatment effect was only active for about a 2-year period, and a point could be made about there being some salary stickiness, due to factors such as the uncertainty about the longevity of the treatment. As such, effects may have been greater if the treatment was active for a longer time.

Perhaps the strongest argument against observable effects on salary is that the existence of BB Sophia coincided with Stockholm County Council stimulus package for specialist nurses. The key assumption is that the stimulus package affected inpatient midwives and intensive care nurses in similar ways. Unfortunately, there are no comprehensive reports on the implementation and effect of the stimulus package, and the conditions for the stimulus package reportedly became open for interpretation. Therefore, it is difficult to completely reject the possibility that our observed effects are explained by differential effects of the stimulus package.

In addition, one would expect that lower employer concentration for inpatient midwives would also spillover to benefit outpatient midwives, however we see no such effects when outpatient midwife salaries are compared to psychiatry nurses as control (both unaffected by the stimulus package). It is worth noting that expected spillover effects for inpatient midwives were small, and the smaller sample size for inpatient midwives could make potential effects difficult to measure. Additionally, while both midwife groups have the same training, their work is very different, suggesting that there may be a substantial threshold for switching between groups. This is supported by the observation that no midwives switched between inpatient and outpatient workplaces in our dataset during the entire 2010–2018 period. Although it is worth noting that our data is based on payroll data on January 1 of every year, and therefore our results do not exclude the possibility of back and forth changes during the year. As such, while an observable spillover effect in outpatient midwives would have strengthened the effects seen in inpatient midwives, there are a number of plausible reasons as to why no effects can be seen that do not contradict results of higher salaries for inpatient midwives.

8.3.2 Employment

While there is an overall increase in employment of midwives in Stockholm county that can be seen in conjunction with the opening of BB Sophia, the number of employed midwives in the public sector decrease in time with opening of BB Sophia (Figure 8). Strictly speaking, classical monopsony predicts that the employment level should increase even in the public sector, due to lower marginal factor cost. However, looking closer at the assumptions of the competitive fringe scenario of classical monopsony, there are assumptions regarding the supply and demand curves of the dominant firm vis-à-vis the competitive fringe which may not hold, at least in the short-term. For example, BB Sophia, was only equipped to employ a set number of inpatient midwives, at least in the short run. In other words, there may be short-term demand constraint, where the short-term demand = 0 for any more than 60 inpatient midwives.

Furthermore, the demand curve is assumed to be steeper for the fringe than for the dominant firm due to assumed lower efficiency due to smaller scale, less experience, know-how, etc. In fact, we know that since the private maternity wards such as BB Sophia are financed by the county council in the same way as public hospitals, the revenue constraint is similar. Therefore, it is only possible to maximize profit by reducing costs. However, private sector hospitals and wards have greater ability to minimize costs, such as through lowering personnel training costs, hiring more experienced employees, and selecting patients that are less costly to care for. As such, this greater ability to decrease costs may instead mean that private health clinics may have higher demand for nurses, although only up to a certain number of nurses, at least in the short-term; a feature not represented in the classical monopsony model.

Classical monopsony also assumes that there is no labor supply constraint. In fact, classical monopsony has traditionally been used to explain staffing shortages despite plenty of labor supply. This assumption may not hold short-term, as it takes time to train nurses and there may be short-term thresholds for attracting nurses from other labor markets. We observe that the number of inpatient midwives employed decreases during the period that BB Sophia was open, although the number of midwives working in the healthcare sector overall increases in Stockholm during the same period. This would suggest that there is some supply constraint, at least short-term.

8.3.3 Synthesis

Individual salaries for publicly employed inpatient midwives are observed to increase and decrease after the opening and closing of private maternity wards, respectively, as compared to controls. After the opening of the private maternity ward BB Sophia, the number of publicly employed midwives decrease, however increase for the private sector and overall in Stockholm county.

The economic significance of the salary difference for inpatient nurses is estimated to about 0.3% for the opening of maternity ward BB Sophia, which translates to approximately 100 SEK per month. While it is unlikely that 100 SEK per month is sufficient to increase employment levels in the labor market, this is an average number for all public sector inpatient midwives and there may be numerous reasons as to why our data may not capture the full extent of potential salary increases, as elaborated above.

In line with the classical monopsonistic model with a dominant firm (public sector) and a competitive fringe (private maternity ward), salaries increase in the dominant firm, and employment increases in the labor market. While employment levels in the dominant firm decreases, this contradicts only the dominant firm and competitive fringe model, and not that there are monopsonistic powers in principle. In fact, we argue that the underlying assumptions on the shape of the demand curve of the fringe and lack of short-term supply constraint may adequately explain why employment levels decrease for the dominant firm. Keeping in mind challenges such as a coinciding stimulus package, we therefore cautiously interpret our results to be in support for nursing labor markets in Stockholm departing from a competitive labor market and in some support for classical monopsony.

While previous quasi-experimental studies have studied either the effect of changes in salary on employment or vice versa, our study studies the effect of both salary and employment in the event of new employer entry and employer exit. Other important differences are that previous studies are set in the United States, where labor unions in general have substantially less power, and private hospitals are not publicly funded as in Sweden. Still, while Staiger et al. (2010) showed support for monopsony in nursing labor markets., Matsuidara (2014) could show no such effects in nursing aide labor markets. As such, this leaves little guidance in the literature. Furthermore, we are able to observe essentially two events, both the entry and exit of the maternity wards, although we had only salary for after the exit for the maternity wards, as we lacked data for employment levels. As far as we know, our study is the most in-depth econometrical analysis of a change in employer concentration on salaries and employment in nursing labor markets in the context of classical monopsonistic effects.

8.4 Strengths and weaknesses

Major strengths of our study are the use of a natural experiment, as well as well-defined and apt treatment and control groups. Previous studies have either not used control groups or often non-nurses or other cities or states as control. Here, we use, arguably, the best possible control group: a different group of nurses in the same city during the same time without any overlap with the treatment group.

In addition, we use a detailed individual-level dataset of all publicly employed nurses in the entire Stockholm labor market. This enables us to use individual fixed-effects that allows precise estimation of even small effects. As the data is based on administrative payroll data, it has been collected systematically and is subjected to regular controls. Therefore, our data may be expected to be more accurate in comparison with survey data or hospital-average salaries used in other quasi-experimental studies.

Weaknesses in our study include only being able to use one treatment and control group. Ideally, more nursing categories would have made for suitable control groups in sensitivity analyses. However, this was not possible due to the coinciding stimulus package, leaving only intensive care nurses (and oncology nurses) as a suitable control. Although we had some secondary treatment and control groups, certainly if the effects could be replicated in even more apt control-treatment groups, this would add to the robustness of our results.

Furthermore, we only had access to detailed salary and employment data for the public sector, and only had aggregate-level data for the private sector. This limits our analyses to effects on salary to those employed by the public sector. More detailed data on private sector salaries would certainly more informative, and allow market-wide analyses.

Analyses on employment information in general were also mainly descriptive, as we only had access to data on an aggregate-level. Furthermore, this data encompassed Norrtälje and Södertälje hospitals as well, which were beyond our market definition, although they are smaller and effects can be assumed to be small.

9 Conclusion

Our findings are consistent with the hypothesis that affected nursing categories (inpatient midwives) would experience relatively increased salary when the private maternity ward BB Sophia was open, compared to before BB Sophia opened and to unaffected nursing categories. Furthermore, our results are consistent with the hypothesis that relative salaries would decrease for affected nursing categories after BB Sophia and Södra BB closed, compared to when BB Sophia and Södra BB were open and to unaffected nursing categories. For the opening of BB Sophia, our results show a 0.3% increase in relative salary and for the closing of the maternity the relative salary was decreased with -0.4%. While the magnitude of observed effects is small, our data does not take non-recurring compensation and staffing nurses into consideration, which may underestimate the effects. Furthermore, sensitivity analyses support that key assumptions are met.

A complicating factor was the coincidental Stockholm Council County stimulus package received by specialist nurses (including both the treatment and control groups), which may have had differential effects for our treatment and control groups resulting in observed results. However, our findings are replicable using secondary treatment and control groups in our sensitivity analysis, and hold for the closing of the maternity wards as well.

While employment levels increase overall for midwives in Stockholm county in line with our model, they decrease amongst public sector employers. In the classical monopsonistic model with a dominant firm and competitive fringe, employment in the public sector should increase with the market entry of a competitive fringe. However, this is based on assumptions on the shape of the fringe demand curve and assumes that there are no short-run labor supply limits, and does not contradict monopsony per se. Arguably, the overall employment trend is more informative, and is therefore also in support of monopsonistic models.

Future extensions may benefit from additional data from private employers, more in-depth analysis and case-study of the stimulus package, more detailed employment data, as well as models and data that allow non-recurring payments and staffing nurses to be considered, such as taxation data and annual reports on staffing costs. Incorporating these additional aspects may contribute to a better understanding of nursing labor markets.

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Appendix 1. List of variables

Name	Definition	Unit
PERSON_REF	Unique IDs per person (for tracing individuals)	
ANSTAELLNING_REF	Employment contract Ids	
AALDER	Age	Years
KOEN	Gender	Female/Male
FOM	Date of contract start	Year-Month-Day
TOM	Date of contract end	Year-Month-Day
KRONTALSLOENHELT	Monthly salary	SEK (nominal)
LOENETILLAEGGHELT	Bonus	SEK (nominal)
ANSTFORMBEN	Employment type (full-time, part-time, substitute, general fixed-term employment, other)	
SYSSGRAD	Employment level (where 100 is full-time)	0-100
HELTIDSMATT	Full-time measurement (number of hours equivalent to a full-time position given the employment type)	Hours per year
FMGRPBEN	Employment type in terms of full- or part-time (full-time, part-time, additional comments)	
KATEGORI	Profession code unique to the profession (i.e. nursing categories, biomedical analyst)	
KATEGORIBEN	Profession (i.e., nursing categories, biomedical analyst)	
ETIKETT	Profession code unique to the profession (i.e. nursing categories, biomedical analyst)	
ORG_REF	Organization reference, code unique to the department of the workplace	Code
ORGBEN	Organization name (i.e. name of clinic, hospital etc.)	
ORGSPEC_BEN	Name of employer	

Note that KATEGORI and ETIKETT codes are not identical

Appendix 2. Median Salary (S.D.) / No. Employeed*

Nursing Category	2010	2011	2012	2013	2014	2015	2016	2017	2018
Ambulance	27272 (1522) / 91	27800 (1501) / 93	28370 (1470) / 96	28885 (1072) / 110	29720 (1109) / 129	30785 (1149) / 132	32160 (1161) / 140	33315 (1172) / 140	34800 (1548) / 157
Inpatient Midwives	30000 (3807) / 819	30500 (3919) / 846	31250 (3861) / 865	31700 (3691) / 836	33456 (4053) / 862	35500 (4292) / 835	36176.5 (4315) / 816	36300 (4491) / 851	37500 (4708) / 808
Outpatient Midwives	28900 (1286) / 194	29500 (1345) / 189	30000 (1379) / 187	30600 (1567) / 191	31300 (1734) / 191	32175 (1766) / 180	33100 (1708) / 189	33825 (1749) / 198	34500 (1789) / 193
District	29000 (2548) / 513	29600 (2616) / 495	30200 (2525) / 493	31100 (2224) / 490	32000 (2170) / 492	33000 (2137) / 505	34000 (2220) / 492	35000 (2061) / 480	36070 (1965) / 440
Registered Nurse	25100 (3318) / 5710	25397 (3478) / 5912	26050 (3629) / 6164	26300 (3616) / 6177	27350 (3638) / 6040	28800 (3699) / 6118	29500 (3803) / 6020	30300 (4081) / 5948	31500 (4304) / 5901
Intensive Care (ICU)	30100 (2984) / 576	30550 (3113) / 602	31600 (3628) / 620	31900 (3584) / 637	33475 (3984) / 656	35725 (4347) / 624	36400 (4293) / 621	37000 (4365) / 609	38500 (4401) / 563
Anesthesiology	29600 (2922) / 418	30100 (3049) / 443	31300 (3312) / 462	31700 (3346) / 466	33600 (3807) / 457	35300 (4113) / 462	36000 (4105) / 468	36625 (4049) / 466	38000 (3742) / 449
Pediatrics	28400 (2398) / 584	29000 (2457) / 608	30000 (2610) / 607	30500 (2544) / 603	31550 (3021) / 628	33100 (3233) / 612	33900 (3279) / 645	34750 (3348) / 616	35784.5 (3573) / 630
Geriatrics	24750 (3212) / 126	25630 (3201) / 92	26100 (4016) / 21	26515 (3717) / 20	27000 (3804) / 19	27600 (4902) / 23	29400 (4695) / 21	30150 (4682) / 18	33653.5 (3236) / 14
Oncology	28600 (2669) / 119	30000 (2814) / 117	31150 (2749) / 119	31300 (3071) / 125	32800 (2832) / 213	34350 (3032) / 218	35215 (3153) / 194	35640 (3233) / 198	36700 (3331) / 176
Surgical (OR)	30000 (2811) / 375	30500 (3020) / 386	32000 (3310) / 380	32250 (3621) / 390	34000 (4306) / 409	36000 (4628) / 405	36600 (4699) / 393	37300 (4756) / 407	39500 (4504) / 381
Psychiatry	28900 (2672) / 542	29500 (2799) / 525	30100 (2702) / 531	30976 (2685) / 509	31850 (2828) / 475	32800 (3095) / 459	33900 (3289) / 457	34550 (3225) / 437	35800 (3569) / 413
Radiology	26600 (3522) / 374	27200 (3708) / 378	28376 (3884) / 385	28600 (3997) / 385	29200 (4369) / 388	30000 (4558) / 412	30500 (4557) / 402	31300 (4792) / 400	32800 (4783) / 397
Ophtamology	28250 (2828) / 58	29175 (2907) / 58	29480 (3117) / 60	30700 (3118) / 61	31250 (2896) / 58	31500 (3324) / 58	32500 (3403) / 56	33500 (3337) / 52	34500 (3167) / 49

*Includes full-time, part-time, permanent and temporary contracts. Part-time salaries calculated as full-time equivalents.

Appendix 3 – Interviews

Ingrid Allerstam, board member within region Stockholm at Vårdförbundet, (The Swedish Association of Health Professionals).
Account from an interview conducted at Karolinska Institutiet *(in person) on April 25, and followed up by e-mail communication.*

- The implementation of the stimulus program offered by SLL in 2014–2015 was different at different workplaces. Its purpose was to increase salaries for well-performing staff (and increase wage discrimination). However, some employers used the extra money to flatten out differences in salary.

- Hospitals have seen an increasing use of relatively expensive, temporarily hired staff, overtime monetary compensation, and extra shift monetary compensations over time.

- In 2017, Karolinska University Hospital introduced the role “assistant university nurse” and “university nurse”, a more senior and advanced role for nurses.

- Karolinska University Hospital had two-year spanning wage contracts that had been formulated between *Vårdförbundet* and the hospital during 2011-04-01 to 2013-04-30. Salary growth for the entire period was encompassed in the first year.

- An anonymous source claimed that Danderyd Hospital offered a salary-increase of SEK 2000 for midwives that stayed at Danderyd when BB Sophia opened. This was outside of the Union’s negotiations.

Kajsa Westlund, Barnmorskeförbundet (The Swedish Association of Midwives)

Account from a telephone interview conducted on March 28, 2018.

- The closing of OB/gynecology ward Södra BB was late in 2016 or early 2017 where around 25 to 50 midwives were hired within the OB and maternity functions. There were no big changes in OB/maternity care out of the ordinary between 2014 and 2016, but BB Sophia was an exceptional event.
- Earlier on, more people used to switch from maternity wards to outpatient midwifery clinics. But since five to ten years ago, it is more common to start directly in outpatient midwifery clinics. The working hours are better in outpatient care, which can make it difficult to switch in the opposite direction.
- Some outpatient midwives might take extra shifts in inpatient maternity wards.
- The concept embodied in Södra BB moved to Södertälje, and some nurses decided to continue working in Södertälje instead.
- No readily available data on staffing midwives

Gudrun Abascal, founder of BB Sophia.

Account from a telephone interview conducted on March 28, 2018.

- Planning for BB Sophia started in 2011, and recruitment process begun in September or October 2013. The maternity ward did not recruit through higher wages – the prevailing market wage was taken as granted. There was no ambition to use wages as an argument for recruitment.
- About 200 applications were received and 60–65 midwives were recruited. The policy was that a third of the recruits would be recently graduated midwives, a second third those with medium experience (five to ten years), and the last third experienced midwives with ten to fifteen years and more of experience.
- The maternity ward also hired neonatal nurses, surgical nurses and anesthesiology nurses.

Appendix 4 – Full regression outputs for Table 4

STATA Statistics/Data Analysis

```
      name:  <unnamed>
       log:  C:\Users\tamin\Dropbox\EXAMENSARBETE\STATA analyser\20180420\log1.smcl
  log type:  smcl
 opened on:  12 May 2018, 11:37:42

1 . /*FE*/
2 . xtreg salary_log time treated did if import_year>= 2013 & import_year<=2016 & (kateg
> oriben == "Barnmorska" | kategoriben == "Sjuksköterska IVA"), fe robust /*individual
>  fixed effects*/
note: treated omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,887
Group variable: person_ref                      Number of groups  =      2,054

R-sq:                                           Obs per group:
     within  = 0.6382                                         min =          1
     between = 0.0373                                         avg =        2.9
     overall = 0.1396                                         max =          4

                                                F(2,2053)         =    2794.34
corr(u_i, Xb)  = -0.0358                        Prob > F          =     0.0000

                         (Std. Err. adjusted for 2,054 clusters in person_ref)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   .0426215   .0008769    48.61   0.000     .0409018    .0443411
     treated |          0  (omitted)
         did |   .0034889    .001195     2.92   0.004     .0011455    .0058324
       _cons |   4.512151   .0002936  1.5e+04   0.000     4.511575    4.512727
-------------+----------------------------------------------------------------
     sigma_u |   .0503361
     sigma_e |  .01840922
         rho |   .8820244   (fraction of variance due to u_i)
------------------------------------------------------------------------------

3 . xtreg salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt treated d
> id if import_year>= 2013 & import_year<=2016 & (kategoriben == "Barnmorska" | katego
> riben == "Sjuksköterska IVA"), fe robust /*with corrections*/
note: 2220.heltidsmatt omitted because of collinearity
note: treated omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,887
Group variable: person_ref                      Number of groups  =      2,054

R-sq:                                           Obs per group:
     within  = 0.6855                                         min =          1
     between = 0.4092                                         avg =        2.9
     overall = 0.4288                                         max =          4

                                                F(13,2053)        =          .
corr(u_i, Xb)  = 0.2005                         Prob > F          =          .

                           (Std. Err. adjusted for 2,054 clusters in person_ref)
--------------------------------------------------------------------------------
               |               Robust
    salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
          time |   .0393206   .0008164    48.17   0.000     .0377197    .0409216
               |
  age_category |
            2  |   .0167814   .0032172     5.22   0.000     .0104721    .0230906
            3  |   .0320518   .0037164     8.62   0.000     .0247635    .0393401
            4  |   .0463338   .0047856     9.68   0.000     .0369487    .0557189
               |
 1.tillsvidare |  -.0042401   .0014513    -2.92   0.004    -.0070862    -.001394
      1.heltid |   .0084128    .002148     3.92   0.000     .0042002    .0126253
               |
   heltidsmatt |
         2045  |   -.013471   .0156024    -0.86   0.388    -.0440692    .0171272
```

```
        2060  |  -.0026923   .0025727    -1.05   0.295    -.0077376    .0023531
        2078  |  -.0185764   .0027932    -6.65   0.000    -.0240541   -.0130986
        2180  |   .0037565   .0037121     1.01   0.312    -.0035234    .0110363
        2220  |          0  (omitted)
        2250  |  -.0318407   .0038687    -8.23   0.000    -.0394277   -.0242537
        2295  |  -.0252314   .0024587   -10.26   0.000    -.0300532   -.0204096
        2340  |  -.0374867   .0024147   -15.52   0.000    -.0422222   -.0327511
        2370  |   -.005326     .00244    -2.18   0.029    -.0101111   -.0005408
        2400  |  -.0099033   .0038362    -2.58   0.010    -.0174264   -.0023801
              |
      treated |          0  (omitted)
          did |   .0038745   .0011085     3.50   0.000     .0017006    .0060484
        _cons |   4.488419   .0045136   994.41   0.000     4.479568    4.497271
-------------+----------------------------------------------------------------
      sigma_u |  .04085006
      sigma_e |  .01719644
          rho |  .84946506   (fraction of variance due to u_i)
------------------------------------------------------------------------------

4 . xtreg salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt i.import_
> year treated did if import_year>= 2013 &  import_year<=2016 & (kategoriben == "Barnm
> orska" | kategoriben == "Sjuksköterska IVA"), fe robust /*year variable*/
note: 2220.heltidsmatt omitted because of collinearity
note: 2016.import_year omitted because of collinearity
note: treated omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,887
Group variable: person_ref                      Number of groups  =      2,054

R-sq:                                           Obs per group:
     within  = 0.8076                                         min =          1
     between = 0.2394                                         avg =        2.9
     overall = 0.3393                                         max =          4

                                                F(15,2053)        =          .
corr(u_i, Xb)  = 0.1102                         Prob > F          =          .

                           (Std. Err. adjusted for 2,054 clusters in person_ref)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   .0586815   .0009367    62.64   0.000     .0568445    .0605186
             |
age_category |
          2  |   .0095046   .0027348     3.48   0.001     .0041414    .0148678
          3  |   .0168897   .0032274     5.23   0.000     .0105603    .0232191
          4  |   .0223485   .0043252     5.17   0.000     .0138663    .0308307
             |
1.tillsvidare |  -.0048986   .0012722    -3.85   0.000    -.0073937   -.0024036
    1.heltid |   .0060341   .0019175     3.15   0.002     .0022736    .0097945
             |
 heltidsmatt |
        2045 |  -.0130344   .0151294    -0.86   0.389     -.042705    .0166361
        2060 |  -.0013013   .0022895    -0.57   0.570    -.0057914    .0031887
        2078 |  -.0201581   .0025338    -7.96   0.000    -.0251271   -.0151891
        2180 |   .0070632   .0031485     2.24   0.025     .0008885    .0132378
        2220 |          0  (omitted)
        2250 |  -.0304982   .0032801    -9.30   0.000    -.0369308   -.0240655
        2295 |  -.0221768   .0022413    -9.89   0.000    -.0265723   -.0177814
        2340 |  -.0271099   .0022627   -11.98   0.000    -.0315473   -.0226725
        2370 |  -.0048167   .0022454    -2.15   0.032    -.0092202   -.0004131
        2400 |  -.0110864   .0035775    -3.10   0.002    -.0181023   -.0040705
             |
 import_year |
        2014 |   .0244365   .0004602    53.10   0.000     .0235341     .025339
        2015 |  -.0083399   .0003722   -22.41   0.000    -.0090699   -.0076099
        2016 |          0  (omitted)
             |
     treated |          0  (omitted)
         did |   .0034471   .0010803     3.19   0.001     .0013285    .0055657
       _cons |   4.494158   .0039571  1135.72   0.000     4.486398    4.501918
```

sigma_u	.04493833
sigma_e	.01345343
rho	.91774638 (fraction of variance due to u_i)

```
5 . xtreg salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt i.import_
> year treated did if import_year>= 2013 &  import_year<=2016 & (kategoriben == "Barnm
> orska" | kategoriben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onkologi
> "), fe robust /*year variable*/
note: 2220.heltidsmatt omitted because of collinearity
note: 2016.import_year omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      6,637
Group variable: person_ref                      Number of groups  =      2,322

R-sq:                                           Obs per group:
     within  = 0.7997                                         min =          1
     between = 0.2051                                         avg =        2.9
     overall = 0.3066                                         max =          4

                                                F(15,2321)        =          .
corr(u_i, Xb)  = 0.0674                         Prob > F          =          .

                            (Std. Err. adjusted for 2,322 clusters in person_ref)
```

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time	.0564093	.0008506	66.32	0.000	.0547413	.0580773
age_category						
2	.0101843	.002696	3.78	0.000	.0048974	.0154711
3	.0180971	.0031849	5.68	0.000	.0118515	.0243427
4	.0224459	.0040993	5.48	0.000	.0144073	.0304845
1.tillsvidare	-.0067032	.0012525	-5.35	0.000	-.0091593	-.0042471
1.heltid	.0063841	.0018361	3.48	0.001	.0027834	.0099847
heltidsmatt						
2045	-.0135176	.0151193	-0.89	0.371	-.0431664	.0161311
2060	-.001037	.0022714	-0.46	0.648	-.0054912	.0034172
2078	-.0178254	.0024747	-7.20	0.000	-.0226782	-.0129726
2180	.0058303	.0031697	1.84	0.066	-.0003855	.0120461
2220	0	(omitted)				
2250	-.0322045	.0033092	-9.73	0.000	-.0386939	-.0257151
2295	-.0220632	.0021968	-10.04	0.000	-.0263711	-.0177552
2340	-.0289396	.0022006	-13.15	0.000	-.0332549	-.0246243
2370	-.0048402	.0022076	-2.19	0.028	-.0091693	-.000511
2400	-.0130398	.0033722	-3.87	0.000	-.0196527	-.0064269
import_year						
2014	.0239732	.0004438	54.01	0.000	.0231028	.0248435
2015	-.0083955	.0003422	-24.53	0.000	-.0090667	-.0077244
2016	0	(omitted)				
treated	-.0074754	.0008317	-8.99	0.000	-.0091065	-.0058444
did	.0056526	.0010172	5.56	0.000	.003658	.0076473
_cons	4.498203	.003957	1136.78	0.000	4.490443	4.505962
sigma_u	.04465928					
sigma_e	.01332669					
rho	.91823375	(fraction of variance due to u_i)				

```
6 . xtreg salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt i.import_
  > year treated did if import_year>= 2013 &  import_year<=2016 & (treated == 1 | katego
  > riben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onkologi"), fe robust/*
  > year variable*/
  note: 2220.heltidsmatt omitted because of collinearity
  note: 2016.import_year omitted because of collinearity

  Fixed-effects (within) regression               Number of obs     =     12,575
  Group variable: person_ref                      Number of groups  =      4,513

  R-sq:                                           Obs per group:
       within  = 0.7961                                         min =          1
       between = 0.1935                                         avg =        2.8
       overall = 0.3021                                         max =          4

                                                  F(17,4512)        =          .
  corr(u_i, Xb)  = 0.0736                         Prob > F          =          .

                          (Std. Err. adjusted for 4,513 clusters in person_ref)
  ------------------------------------------------------------------------------
               |               Robust
    salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
  -------------+----------------------------------------------------------------
          time |    .057073    .000773    73.83   0.000     .0555575    .0585885
               |
  age_category |
            2  |   .0096524   .0021362     4.52   0.000     .0054643    .0138405
            3  |   .0156967   .0025145     6.24   0.000     .0107671    .0206264
            4  |   .0196293   .0029478     6.66   0.000     .0138501    .0254085
               |
 1.tillsvidare |   -.007524   .0009036    -8.33   0.000    -.0092956   -.0057525
      1.heltid |   .0051811   .0014108     3.67   0.000     .0024151     .007947
               |
   heltidsmatt |
         2045  |  -.0108527    .016127    -0.67   0.501    -.0424695     .020764
         2060  |  -.0007806   .0020707    -0.38   0.706    -.0048402     .003279
         2078  |  -.0177468   .0022727    -7.81   0.000    -.0222023   -.0132912
         2180  |     .00889   .0025732     3.45   0.001     .0038454    .0139347
         2220  |          0  (omitted)
         2250  |  -.0352815   .0030826   -11.45   0.000    -.0413249   -.0292382
         2295  |  -.0224031   .0017609   -12.72   0.000    -.0258552   -.0189509
         2340  |  -.0172358   .0040723    -4.23   0.000    -.0252195   -.0092522
         2370  |  -.0024155   .0017712    -1.36   0.173    -.0058879    .0010569
         2400  |  -.0126885   .0022122    -5.74   0.000    -.0170255   -.0083515
               |
   import_year |
         2014  |    .024487   .0003348    73.14   0.000     .0238306    .0251434
         2015  |  -.0088536   .0002245   -39.44   0.000    -.0092937   -.0084135
         2016  |          0  (omitted)
               |
       treated |  -.0040342   .0040606    -0.99   0.321    -.0119951    .0039266
           did |   .0027103   .0008104     3.34   0.001     .0011216     .004299
         _cons |    4.49675   .0041384  1086.60   0.000     4.488636    4.504863
  -------------+----------------------------------------------------------------
       sigma_u |  .04419158
       sigma_e |  .01330126
           rho |  .91693026   (fraction of variance due to u_i)
  ------------------------------------------------------------------------------

7 .
```

```
8 .
9 . /*pooled OLS*/
10. regress salary_log time treated did if import_year>= 2013 & import_year<=2016 & (kat
  > egoriben == "Barnmorska" | kategoriben == "Sjuksköterska IVA"), robust /*individual
  > fixed effects*/
```

```
Linear regression                               Number of obs     =      5,887
                                                F(3, 5883)        =     319.47
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1401
                                                Root MSE          =     .05111
```

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time	.039958	.002041	19.58	0.000	.0359568	.0439592
treated	-.0021603	.0018717	-1.15	0.248	-.0058295	.0015088
did	.0022395	.0026948	0.83	0.406	-.0030433	.0075224
_cons	4.515041	.0013987	3228.14	0.000	4.512299	4.517782

```
11. regress salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt treated
  >  did if import_year>= 2013 & import_year<=2016 & (kategoriben == "Barnmorska" | kate
  > goriben == "Sjuksköterska IVA"), robust cluster(orgben) /*with corrections*/
```

```
Linear regression                               Number of obs     =      5,887
                                                F(14, 135)        =          .
                                                Prob > F          =          .
                                                R-squared         =     0.4938
                                                Root MSE          =     .03926

                                (Std. Err. adjusted for 136 clusters in orgben)
```

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time	.0378249	.0019036	19.87	0.000	.0340602	.0415895
age_category						
2	.0205832	.0021767	9.46	0.000	.0162783	.0248881
3	.0419638	.002973	14.11	0.000	.0360841	.0478435
4	.0822373	.0030474	26.99	0.000	.0762106	.0882641
1.tillsvidare	-.0101104	.0039677	-2.55	0.012	-.0179572	-.0022635
1.heltid	.0065012	.0019485	3.34	0.001	.0026476	.0103547
heltidsmatt						
2045	.0316257	.005099	6.20	0.000	.0215414	.04171
2060	-.0048752	.0048622	-1.00	0.318	-.0144912	.0047409
2078	.005353	.0045796	1.17	0.245	-.003704	.01441
2180	.0011864	.0052855	0.22	0.823	-.0092667	.0116394
2220	-.0390885	.0049448	-7.91	0.000	-.0488677	-.0293092
2250	-.0348429	.009597	-3.63	0.000	-.0538228	-.015863
2295	-.0325663	.0045458	-7.16	0.000	-.0415565	-.0235761
2340	.0026508	.0046085	0.58	0.566	-.0064634	.0117649
2370	.0220692	.0156152	1.41	0.160	-.0088129	.0529513
2400	-.0079999	.0048185	-1.66	0.099	-.0175295	.0015296
treated	.0008049	.003955	0.20	0.839	-.0070169	.0086267
did	.0025974	.0024285	1.07	0.287	-.0022054	.0074002
_cons	4.473678	.0055079	812.23	0.000	4.462785	4.484571

```
12. regress salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt i.impor
  > t_year treated did if import_year>= 2013 &  import_year<=2016 & (kategoriben == "Bar
  > nmorska" | kategoriben == "Sjuksköterska IVA"), robust cluster(orgben) /*year variab
  > le*/
  note: 2016.import_year omitted because of collinearity

  Linear regression                               Number of obs     =      5,887
                                                  F(16, 135)        =          .
                                                  Prob > F          =          .
                                                  R-squared         =     0.5124
                                                  Root MSE          =     .03854

                                (Std. Err. adjusted for 136 clusters in orgben)
```

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time	.0515185	.0020061	25.68	0.000	.047551	.055486
age_category						
2	.020599	.0022039	9.35	0.000	.0162404	.0249576
3	.0421079	.0029852	14.11	0.000	.0362041	.0480118
4	.0822328	.0029605	27.78	0.000	.0763779	.0880877
1.tillsvidare	-.0101047	.0040437	-2.50	0.014	-.018102	-.0021075
1.heltid	.006244	.0019237	3.25	0.001	.0024396	.0100484
heltidsmatt						
2045	.0306363	.0050542	6.06	0.000	.0206406	.0406321
2060	-.0047176	.0048259	-0.98	0.330	-.0142617	.0048266
2078	.0056495	.0045151	1.25	0.213	-.00328	.014579
2180	.0022832	.0053329	0.43	0.669	-.0082637	.0128301
2220	-.0287015	.0046331	-6.19	0.000	-.0378644	-.0195385
2250	-.0339531	.0097491	-3.48	0.001	-.0532339	-.0146723
2295	-.0322853	.0044643	-7.23	0.000	-.0411144	-.0234562
2340	.0042643	.0045548	0.94	0.351	-.0047438	.0132724
2370	.0225581	.015639	1.44	0.151	-.0083709	.0534872
2400	-.0078765	.0047716	-1.65	0.101	-.0173132	.0015603
import_year						
2014	.0198386	.0011566	17.15	0.000	.0175511	.022126
2015	-.0072062	.001018	-7.08	0.000	-.0092195	-.0051929
2016	0	(omitted)				
treated	.000754	.0039064	0.19	0.847	-.0069716	.0084796
did	.0026493	.002368	1.12	0.265	-.002034	.0073325
_cons	4.463547	.0053138	839.99	0.000	4.453038	4.474056

```
13. regress salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt i.impor
  > t_year treated did if import_year>= 2013 &  import_year<=2016 & (kategoriben == "Bar
  > nmorska" | kategoriben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onkolo
  > gi"), robust cluster(orgben) /*year variable*/
  note: 2016.import_year omitted because of collinearity

  Linear regression                               Number of obs     =      6,637
                                                  F(16, 179)        =          .
                                                  Prob > F          =          .
                                                  R-squared         =     0.4772
                                                  Root MSE          =     .03897
```

(Std. Err. adjusted for 180 clusters in orgben)

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time	.0495618	.001738	28.52	0.000	.0461323	.0529913
age_category						
2	.0204458	.0022399	9.13	0.000	.0160259	.0248658
3	.0428778	.0028257	15.17	0.000	.0373019	.0484537
4	.080709	.0028664	28.16	0.000	.0750527	.0863653
1.tillsvidare	-.0132496	.0036892	-3.59	0.000	-.0205295	-.0059696
1.heltid	.0073793	.0019775	3.73	0.000	.003477	.0112816
heltidsmatt						
2045	.0284277	.0049715	5.72	0.000	.0186175	.038238
2060	.0001395	.0044356	0.03	0.975	-.0086132	.0088922
2078	.0128599	.0040305	3.19	0.002	.0049066	.0208133
2180	.004644	.0054775	0.85	0.398	-.0061648	.0154527
2220	-.0236861	.0040241	-5.89	0.000	-.0316269	-.0157454
2250	-.0334068	.0096347	-3.47	0.001	-.0524189	-.0143946
2295	-.0319614	.0043864	-7.29	0.000	-.040617	-.0233057
2340	.009299	.0042087	2.21	0.028	.0009939	.0176041
2370	.0241199	.015697	1.54	0.126	-.0068551	.055095
2400	-.0203938	.0044814	-4.55	0.000	-.0292369	-.0115508
import_year						
2014	.0190694	.0010897	17.50	0.000	.016919	.0212197
2015	-.0076831	.0009602	-8.00	0.000	-.0095779	-.0057883
2016	0	(omitted)				
treated	.0071524	.0037185	1.92	0.056	-.0001853	.0144901
did	.0049206	.002149	2.29	0.023	.00068	.0091612
_cons	4.462065	.0053395	835.68	0.000	4.451529	4.472601

```
14. regress salary_log time i.age_category i.tillsvidare i. heltid i.heltidsmatt i.impor
  > t_year treated did if import_year>= 2013 &  import_year<=2016 & (treated == 1 | kate
  > goriben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onkologi"), robust cl
  > uster(orgben) /*year variable*/
  note: 2016.import_year omitted because of collinearity

  Linear regression                               Number of obs     =     12,575
                                                  F(17, 361)        =          .
                                                  Prob > F          =          .
                                                  R-squared         =     0.4634
                                                  Root MSE          =     .03902
```

(Std. Err. adjusted for 362 clusters in orgben)

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time	.0503714	.0016375	30.76	0.000	.0471511	.0535917
age_category						
2	.0203847	.0018942	10.76	0.000	.0166597	.0241098
3	.0434375	.0021104	20.58	0.000	.0392872	.0475877
4	.0795609	.0022071	36.05	0.000	.0752205	.0839013
1.tillsvidare	-.0147702	.0024325	-6.07	0.000	-.0195538	-.0099866
1.heltid	.0051876	.0018664	2.78	0.006	.0015172	.0088579
heltidsmatt						
2045	.0368474	.0034992	10.53	0.000	.0299661	.0437287
2060	-.0011678	.0039412	-0.30	0.767	-.0089184	.0065828
2078	.0126718	.003466	3.66	0.000	.0058556	.019488
2180	.0033112	.0041184	0.80	0.422	-.0047879	.0114104
2220	-.0229127	.0034363	-6.67	0.000	-.0296703	-.0161551
2250	-.0380546	.0069795	-5.45	0.000	-.0517803	-.024329
2295	-.0306798	.0033331	-9.20	0.000	-.0372345	-.0241251

```
        2340 |   -.040294    .003595   -11.21   0.000    -.0473638   -.0332243
        2370 |   .0351338   .0134711     2.61   0.009     .0086421    .0616254
        2400 |  -.0242623   .0034792    -6.97   0.000    -.0311043   -.0174203
             |
 import_year |
        2014 |   .0205421   .0008574    23.96   0.000      .018856    .0222282
        2015 |  -.0073791   .0005983   -12.33   0.000    -.0085557   -.0062025
        2016 |          0  (omitted)
             |
     treated |   .0001549   .0025968     0.06   0.952    -.0049519    .0052617
         did |   .0021235   .0017106     1.24   0.215    -.0012405    .0054875
       _cons |   4.466152   .0040557  1101.20   0.000     4.458176    4.474128
------------------------------------------------------------------------------

15.
16.
17.
18. /*Regression table*/
19. /*closing  of BB sophia*/
20. gen time2 = (import_year>=2017) & (import_year<=2018)

21. gen treated2 = (kategoriben=="Barnmorska" | kategoriben=="Sjuksköterska barn" | kate
> goriben=="Sjuksköterska operation" | kategoriben=="Sjuksköterska anestesi")

22. gen did2 = time2*treated2

23.
24. /*FE*/
25. xtreg salary_log time2 treated2 did2 if import_year>= 2015 & import_year<=2018 & (ka
> tegoriben == "Barnmorska" | kategoriben == "Sjuksköterska IVA"), fe robust /*individ
> ual fixed effects*/
note: treated2 omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,727
Group variable: person_ref                      Number of groups  =      2,072

R-sq:                                           Obs per group:
     within  = 0.3855                                         min =          1
     between = 0.0058                                         avg =        2.8
     overall = 0.0338                                         max =          4

                                                F(2,2071)         =    1526.91
corr(u_i, Xb)  = -0.0337                        Prob > F          =     0.0000

                           (Std. Err. adjusted for 2,072 clusters in person_ref)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       time2 |   .0248052   .0008704    28.50   0.000     .0230983    .0265121
    treated2 |          0  (omitted)
        did2 |  -.0041077    .000974    -4.22   0.000    -.0060178   -.0021976
       _cons |   4.553133   .0002185  2.1e+04   0.000     4.552704    4.553562
-------------+----------------------------------------------------------------
     sigma_u |  .05125061
     sigma_e |  .01568091
         rho |  .91439875   (fraction of variance due to u_i)
------------------------------------------------------------------------------

26. xtreg salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt treated2
>  did2 if import_year>= 2015 & import_year<=2018 & (kategoriben == "Barnmorska" | kat
> egoriben == "Sjuksköterska IVA"), fe robust /*with corrections*/
note: 2078.heltidsmatt omitted because of collinearity
note: 2370.heltidsmatt omitted because of collinearity
note: treated2 omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,727
Group variable: person_ref                      Number of groups  =      2,072
```

```
R-sq:                                           Obs per group:
     within  = 0.4421                                         min =          1
     between = 0.3342                                         avg =        2.8
     overall = 0.2975                                         max =          4

                                                F(12,2071)        =          .
corr(u_i, Xb)  = 0.2836                         Prob > F          =          .

                            (Std. Err. adjusted for 2,072 clusters in person_ref)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       time2 |   .0234035   .0007264    32.22   0.000     .0219789    .0248282
             |
age_category |
          2  |   .0125463   .0027559     4.55   0.000     .0071417    .0179508
          3  |   .0168863   .0031384     5.38   0.000     .0107316    .0230409
          4  |   .0271706   .0058484     4.65   0.000     .0157013      .03864
             |
1.tillsvidare|  -.0071617   .0011493    -6.23   0.000    -.0094156   -.0049078
    1.heltid |   .0044673    .001943     2.30   0.022     .0006569    .0082778
             |
 heltidsmatt |
       2045  |   -.006614   .0029232    -2.26   0.024    -.0123467   -.0008813
       2060  |  -.0031834   .0026346    -1.21   0.227    -.0083501    .0019833
       2078  |          0  (omitted)
       2180  |   .0076875   .0032962     2.33   0.020     .0012233    .0141518
       2250  |  -.0313546   .0059369    -5.28   0.000    -.0429975   -.0197116
       2295  |  -.0168309   .0021825    -7.71   0.000    -.0211111   -.0125507
       2340  |  -.0138388    .002397    -5.77   0.000    -.0185396   -.0091381
       2370  |          0  (omitted)
       2400  |  -.0117093   .0035647    -3.28   0.001    -.0187001   -.0047185
             |
    treated2 |          0  (omitted)
        did2 |  -.0035842   .0009062    -3.96   0.000    -.0053614    -.001807
       _cons |   4.544972    .004601   987.82   0.000     4.535949    4.553995
-------------+----------------------------------------------------------------
     sigma_u |  .04504751
     sigma_e |  .01496602
         rho |  .90059654   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
27. xtreg salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt i.import
  > _year treated2 did2 if import_year>= 2015 &  import_year<=2018 & (kategoriben == "Ba
  > rnmorska" | kategoriben == "Sjuksköterska IVA"), fe robust/*year variable*/
note: 2078.heltidsmatt omitted because of collinearity
note: 2370.heltidsmatt omitted because of collinearity
note: 2018.import_year omitted because of collinearity
note: treated2 omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,727
Group variable: person_ref                      Number of groups  =      2,072

R-sq:                                           Obs per group:
     within  = 0.6604                                         min =          1
     between = 0.1927                                         avg =        2.8
     overall = 0.2248                                         max =          4

                                                F(14,2071)        =          .
corr(u_i, Xb)  = 0.1600                         Prob > F          =          .
```

(Std. Err. adjusted for 2,072 clusters in person_ref)

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time2	.0403876	.0009271	43.56	0.000	.0385694	.0422058
age_category						
2	.0095981	.0026665	3.60	0.000	.0043687	.0148275
3	.0119108	.0030409	3.92	0.000	.0059472	.0178745
4	.0196304	.0056326	3.49	0.001	.0085843	.0306765
1.tillsvidare	-.0075258	.0009434	-7.98	0.000	-.0093759	-.0056757
1.heltid	.0031162	.001622	1.92	0.055	-.0000647	.006297
heltidsmatt						
2045	-.0134185	.0025855	-5.19	0.000	-.0184889	-.0083481
2060	.0014624	.0022363	0.65	0.513	-.0029233	.0058481
2078	0	(omitted)				
2180	.0081101	.0028835	2.81	0.005	.0024551	.0137651
2250	-.0282541	.0050361	-5.61	0.000	-.0381305	-.0183777
2295	-.0145796	.0018617	-7.83	0.000	-.0182305	-.0109287
2340	-.0069509	.0021136	-3.29	0.001	-.0110959	-.002806
2370	0	(omitted)				
2400	-.0158663	.003158	-5.02	0.000	-.0220596	-.009673
import_year						
2016	.0077986	.0003355	23.25	0.000	.0071407	.0084565
2017	-.0214487	.0005102	-42.04	0.000	-.0224492	-.0204482
2018	0	(omitted)				
treated2	0	(omitted)				
did2	-.0037883	.0008564	-4.42	0.000	-.0054678	-.0021087
_cons	4.546204	.0043892	1035.76	0.000	4.537596	4.554811
sigma_u	.04697658					
sigma_e	.01167925					
rho	.94178706	(fraction of variance due to u_i)				

```
28. xtreg salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt i.import
  > _year treated2 did2 if import_year>= 2015 &  import_year<=2018 & (kategoriben == "Ba
  > rnmorska" | kategoriben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onkol
  > ogi"), fe robust/*year variable*/
  note: 2078.heltidsmatt omitted because of collinearity
  note: 2018.import_year omitted because of collinearity

  Fixed-effects (within) regression               Number of obs     =      6,513
  Group variable: person_ref                      Number of groups  =      2,368

  R-sq:                                           Obs per group:
       within  = 0.6545                                         min =          1
       between = 0.1704                                         avg =        2.8
       overall = 0.2148                                         max =          4

                                                  F(15,2367)        =          .
  corr(u_i, Xb)  = 0.1369                         Prob > F          =          .
```

(Std. Err. adjusted for 2,368 clusters in person_ref)

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time2	.0384648	.0008014	47.99	0.000	.0368932	.0400364
age_category						
2	.0098444	.002556	3.85	0.000	.0048323	.0148565
3	.0125728	.0029394	4.28	0.000	.0068088	.0183369
4	.0202361	.0054433	3.72	0.000	.0095619	.0309103
1.tillsvidare	-.0084565	.0009493	-8.91	0.000	-.0103181	-.0065949
1.heltid	.0033402	.0016116	2.07	0.038	.00018	.0065005

```
 heltidsmatt |
        2045 |  -.0130372   .0027925    -4.67   0.000    -.0185132   -.0075613
        2060 |   .0008478    .002251     0.38   0.706    -.0035663     .005262
        2078 |          0  (omitted)
        2180 |   .0073224   .0028045     2.61   0.009     .0018228    .0128221
        2250 |  -.0295702   .0051259    -5.77   0.000     -.039622   -.0195185
        2295 |   -.014762   .0018705    -7.89   0.000    -.0184301    -.011094
        2340 |  -.0077807   .0021622    -3.60   0.000    -.0120207   -.0035407
        2370 |  -.0092386   .0035921    -2.57   0.010    -.0162826   -.0021946
        2400 |  -.0149568   .0035725    -4.19   0.000    -.0219624   -.0079512
             |
 import_year |
        2016 |   .0077213   .0003063    25.21   0.000     .0071207    .0083218
        2017 |  -.0205594   .0004752   -43.26   0.000    -.0214913   -.0196276
        2018 |          0  (omitted)
             |
    treated2 |   .0143724   .0005823    24.68   0.000     .0132305    .0155142
        did2 |  -.0024311   .0007639    -3.18   0.001    -.0039291   -.0009331
       _cons |   4.537899   .0044615  1017.12   0.000      4.52915    4.546648
-------------+----------------------------------------------------------------
     sigma_u |  .04613397
     sigma_e |  .01158483
         rho |  .94068277   (fraction of variance due to u_i)
------------------------------------------------------------------------------

29. xtreg salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt i.import
  > _year treated2 did2 if import_year>= 2015 &  import_year<=2018 & (treated == 1 | kat
  > egoriben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onkologi"), fe robus
  > t /*year variable*/
  note: 2078.heltidsmatt omitted because of collinearity
  note: 2305.heltidsmatt omitted because of collinearity
  note: 2018.import_year omitted because of collinearity

  Fixed-effects (within) regression               Number of obs     =     12,447
  Group variable: person_ref                      Number of groups  =      4,587

  R-sq:                                           Obs per group:
       within  = 0.6691                                         min =          1
       between = 0.2000                                         avg =        2.7
       overall = 0.2273                                         max =          4

                                                  F(17,4586)        =          .
  corr(u_i, Xb)  = 0.1607                         Prob > F          =          .

                             (Std. Err. adjusted for 4,587 clusters in person_ref)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       time2 |   .0385385   .0007302    52.78   0.000      .037107    .0399699
             |
age_category |
           2 |   .0102891   .0019725     5.22   0.000     .0064221    .0141561
           3 |    .015616    .002321     6.73   0.000     .0110658    .0201663
           4 |   .0192263   .0032212     5.97   0.000     .0129112    .0255414
             |
1.tillsvidare|  -.0085313   .0007595   -11.23   0.000    -.0100203   -.0070423
    1.heltid |   .0023466   .0012511     1.88   0.061    -.0001062    .0047994
             |
 heltidsmatt |
        2045 |  -.0144063   .0018826    -7.65   0.000    -.0180971   -.0107155
        2060 |   .0002656   .0019932     0.13   0.894     -.003642    .0041733
        2078 |          0  (omitted)
        2180 |    .011206   .0018947     5.91   0.000     .0074914    .0149205
        2250 |  -.0285359   .0030637    -9.31   0.000    -.0345421   -.0225296
        2295 |  -.0167448    .001511   -11.08   0.000     -.019707   -.0137826
        2305 |          0  (omitted)
        2340 |  -.0150768   .0032701    -4.61   0.000    -.0214877   -.0086658
        2370 |   .0009082   .0054361     0.17   0.867    -.0097491    .0115656
        2400 |    -.016169   .0021217    -7.62   0.000    -.0203285   -.0120094
```

```
 import_year
        2016     .0080763   .0002135    37.83   0.000     .0076578    .0084949
        2017     -.02014    .0003487   -57.76   0.000    -.0208237   -.0194564
        2018           0  (omitted)

    treated2     .0034958   .0047157     0.74   0.459    -.0057493    .0127408
        did2    -.0010009   .0007087    -1.41   0.158    -.0023902    .0003885
       _cons     4.540608   .0044761  1014.41   0.000     4.531833     4.549383
-------------+----------------------------------------------------------------
     sigma_u    .0454395
     sigma_e   .01141214
         rho    .9406661   (fraction of variance due to u_i)
------------------------------------------------------------------------------

30.
31. /*pooled OLS*/
32. regress salary_log time2 treated2 did2 if import_year>= 2015 & import_year<=2018 & (
  > kategoriben == "Barnmorska" | kategoriben == "Sjuksköterska IVA"), robust cluster(or
  > gben) /*individual fixed effects*/

Linear regression                               Number of obs     =      5,727
                                                F(3, 189)         =      55.40
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0354
                                                Root MSE          =     .05135

                              (Std. Err. adjusted for 190 clusters in orgben)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       time2 |   .0241461   .0025851     9.34   0.000     .0190468    .0292454
    treated2 |   .0000792   .0040819     0.02   0.985    -.0079728    .0081312
        did2 |   -.009581   .0030278    -3.16   0.002    -.0155537   -.0036083
       _cons |   4.554999   .0026745  1703.12   0.000     4.549723    4.560274
------------------------------------------------------------------------------

33. regress salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt treate
  > d2 did2 if import_year>= 2015 & import_year<=2018 & (kategoriben == "Barnmorska" | k
  > ategoriben == "Sjuksköterska IVA"), robust cluster(orgben)/*with corrections*/

Linear regression                               Number of obs     =      5,727
                                                F(14, 189)        =          .
                                                Prob > F          =          .
                                                R-squared         =     0.4295
                                                Root MSE          =     .03954

                              (Std. Err. adjusted for 190 clusters in orgben)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       time2 |   .0250441   .0018568    13.49   0.000     .0213815    .0287068
             |
age_category |
          2  |   .0182261   .0024366     7.48   0.000     .0134197    .0230325
          3  |   .0410134   .0030127    13.61   0.000     .0350706    .0469562
          4  |   .0813227   .0029831    27.26   0.000     .0754383    .0872071
             |
1.tillsvidare|  -.0146067    .003734    -3.91   0.000    -.0219724   -.0072411
    1.heltid |   .0065012   .0017801     3.65   0.000     .0029899    .0100126
             |
 heltidsmatt |
       2045  |   .0427902   .0052678     8.12   0.000     .0323989    .0531815
       2060  |  -.0037276   .0045651    -0.82   0.415    -.0127327    .0052775
       2078  |   .0092674   .0046582     1.99   0.048     .0000786    .0184562
       2180  |   .0022735   .0053385     0.43   0.671    -.0082571    .0128041
       2250  |  -.0371059   .0074516    -4.98   0.000     -.051805   -.0224069
       2295  |  -.0257016    .004577    -5.62   0.000    -.0347301   -.0166731
       2340  |   .0163861   .0046582     3.52   0.001     .0071973    .0255749
       2370  |    .013553   .0114004     1.19   0.236    -.0089355    .0360414
       2400  |  -.0062845   .0050951    -1.23   0.219    -.0163351    .0037661
```

```
    treated2 |   .0027425   .0035593     0.77   0.442    -.0042786    .0097636
        did2 |  -.0072479    .002291    -3.16   0.002    -.0117671   -.0027286
       _cons |   4.512999   .0057773   781.16   0.000     4.501603    4.524395
------------------------------------------------------------------------------
```

```
34. regress salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt i.impo
> rt_year treated2 did2 if import_year>= 2015 &  import_year<=2018 & (kategoriben == "
> Barnmorska" | kategoriben == "Sjuksköterska IVA"), robust cluster(orgben)/*year vari
> able*/
note: 2018.import_year omitted because of collinearity

Linear regression                               Number of obs     =      5,727
                                                F(16, 189)        =          .
                                                Prob > F          =          .
                                                R-squared         =     0.4523
                                                Root MSE          =     .03875

                               (Std. Err. adjusted for 190 clusters in orgben)
------------------------------------------------------------------------------
             |               Robust
  salary_log |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       time2 |   .0397505   .0021395    18.58   0.000     .0355302    .0439708
             |
age_category |
          2  |   .0191902   .0022765     8.43   0.000     .0146995    .0236809
          3  |   .0423645   .0028726    14.75   0.000      .036698     .048031
          4  |   .0828315   .0028862    28.70   0.000     .0771381    .0885248
             |
1.tillsvidare |   -.014418   .0037407    -3.85   0.000    -.0217969    -.007039
    1.heltid |   .0064939   .0017819     3.64   0.000      .002979    .0100089
             |
 heltidsmatt |
       2045  |   .0418487   .0052689     7.94   0.000     .0314553    .0522421
       2060  |  -.0029891   .0045341    -0.66   0.511     -.011933    .0059548
       2078  |   .0092651   .0046664     1.99   0.049     .0000602      .01847
       2180  |   .0021808   .0054398     0.40   0.689    -.0085497    .0129113
       2250  |  -.0366738    .007482    -4.90   0.000    -.0514328   -.0219149
       2295  |  -.0256524   .0045381    -5.65   0.000    -.0346042   -.0167005
       2340  |    .019961   .0048719     4.10   0.000     .0103506    .0295713
       2370  |   .0135202   .0115837     1.17   0.245    -.0093298    .0363703
       2400  |  -.0064879    .005118    -1.27   0.206    -.0165836    .0036079
             |
 import_year |
       2016  |   .0071543   .0010279     6.96   0.000     .0051266     .009182
       2017  |  -.0213034   .0013134   -16.22   0.000    -.0238942   -.0187127
       2018  |          0  (omitted)
             |
    treated2 |   .0029665    .003556     0.83   0.405     -.004048     .009981
        did2 |  -.0074464   .0023008    -3.24   0.001    -.0119849   -.0029079
       _cons |   4.507734   .0056585   796.63   0.000     4.496572    4.518896
------------------------------------------------------------------------------
```

```
35. regress salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt i.impo
> rt_year treated2 did2 if import_year>= 2015 &  import_year<=2018 & (kategoriben == "
> Barnmorska" | kategoriben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onk
> ologi"), robust cluster(orgben)/*year variable*/
note: 2018.import_year omitted because of collinearity

Linear regression                               Number of obs     =      6,513
                                                F(16, 242)        =          .
                                                Prob > F          =          .
                                                R-squared         =     0.4149
                                                Root MSE          =     .03919
```

(Std. Err. adjusted for 243 clusters in orgben)

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time2	.0380669	.0022398	17.00	0.000	.0336548	.042479
age_category						
2	.0192207	.0022809	8.43	0.000	.0147277	.0237138
3	.0424176	.0027788	15.26	0.000	.0369439	.0478913
4	.0811001	.0027038	29.99	0.000	.0757741	.0864262
1.tillsvidare	-.0177772	.0033938	-5.24	0.000	-.0244624	-.011092
1.heltid	.0077874	.0019053	4.09	0.000	.0040344	.0115404
heltidsmatt						
2045	.0383327	.0051297	7.47	0.000	.0282281	.0484372
2060	.0028714	.0041318	0.69	0.488	-.0052675	.0110103
2078	.016142	.0040887	3.95	0.000	.0080881	.0241959
2180	.0055629	.0054998	1.01	0.313	-.0052706	.0163965
2250	-.0346922	.0069794	-4.97	0.000	-.0484404	-.0209439
2295	-.0254332	.0044303	-5.74	0.000	-.0341602	-.0167063
2340	.0270735	.0042485	6.37	0.000	.0187046	.0354423
2370	.0153138	.0117344	1.31	0.193	-.0078008	.0384283
2400	-.0202982	.0046866	-4.33	0.000	-.0295299	-.0110665
import_year						
2016	.0076256	.0009659	7.89	0.000	.005723	.0095282
2017	-.0203782	.0012664	-16.09	0.000	-.0228727	-.0178837
2018	0	(omitted)				
treated2	.0116534	.0034679	3.36	0.001	.0048222	.0184846
did2	-.0062346	.002366	-2.64	0.009	-.0108952	-.001574
_cons	4.504419	.0054461	827.09	0.000	4.493691	4.515146

```
36. regress salary_log time2 i.age_category i.tillsvidare i. heltid i.heltidsmatt i.impo
  > rt_year treated2 did2 if import_year>= 2015 &  import_year<=2018 & (treated == 1 | k
  > ategoriben == "Sjuksköterska IVA" | kategoriben == "Sjuksköterska onkologi"), robust
  >  cluster(orgben) /*year variable*/
note: 2018.import_year omitted because of collinearity

Linear regression                               Number of obs     =     12,447
                                                F(17, 451)        =          .
                                                Prob > F          =          .
                                                R-squared         =     0.4135
                                                Root MSE          =     .03904
```

(Std. Err. adjusted for 452 clusters in orgben)

salary_log	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
time2	.0376875	.0019647	19.18	0.000	.0338264	.0415487
age_category						
2	.0192724	.0018876	10.21	0.000	.0155628	.022982
3	.0414788	.0021071	19.68	0.000	.0373377	.0456198
4	.0792283	.002073	38.22	0.000	.0751543	.0833022
1.tillsvidare	-.0182142	.0022456	-8.11	0.000	-.0226275	-.013801
1.heltid	.0066749	.0017343	3.85	0.000	.0032667	.0100832
heltidsmatt						
2045	.0439417	.0033584	13.08	0.000	.0373417	.0505418
2060	.0010644	.0036019	0.30	0.768	-.0060142	.008143
2078	.0149964	.0034451	4.35	0.000	.0082259	.0217669
2180	.0030831	.0044058	0.70	0.484	-.0055753	.0117415
2250	-.0413943	.0048564	-8.52	0.000	-.0509382	-.0318503
2295	-.0255946	.0032684	-7.83	0.000	-.0320179	-.0191714
2305	-.0840946	.0034204	-24.59	0.000	-.0908166	-.0773727
2340	-.0344502	.0038763	-8.89	0.000	-.042068	-.0268324

```
        2370     .0270375   .0107524     2.51   0.012     .0059065    .0481686
        2400    -.0240663   .0033659    -7.15   0.000    -.0306812   -.0174515

 import_year
        2016     .0072854   .0005988    12.17   0.000     .0061085    .0084622
        2017     -.020292   .0008519   -23.82   0.000    -.0219662   -.0186178
        2018            0  (omitted)

    treated2     .0026736   .0025941     1.03   0.303    -.0024244    .0077715
        did2    -.0016323   .0021243    -0.77   0.443    -.0058071    .0025425
       _cons     4.509156    .004278  1054.02   0.000     4.500748    4.517563
```

```
37.
38. log off
      name:  <unnamed>
       log:  C:\Users\tamin\Dropbox\EXAMENSARBETE\STATA analyser\20180420\log1.smcl
  log type:  smcl
 paused on:  12 May 2018, 11:37:54
```