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THE RETURNS TO NURSING: EVIDENCE FROM A PARENTAL LEAVE PROGRAM

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ABSTRACT

Nurses comprise the largest health profession. In this paper, we measure the effect of nurses on health care delivery and patient health outcomes across sectors. Our empirical strategy takes advantage of a parental leave program, which led to a sudden, unintended, and persistent 12% reduction in nurse employment. Our findings indicate detrimental effects on hospital care delivery as indicated by an increase in 30-day readmission rates and a distortion of technology utilization. The effects for nursing home care are more drastic. We estimate a persistent 13% increase in nursing home mortality among the elderly aged 85 and older. Our results also highlight an unintended negative consequence of parental leave programs borne by providers and patients.

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1 Introduction

Nurses comprise the largest health profession. In the U.S., 3.4 million employed licensed nurses in 2014 represented about 30% of all health professionals.[1] Nurses play an important role in the delivery of health care services in hospital, primary, and nursing home care and are important to the success of emerging patient-oriented care models. Hence, quantifying the effects of nurses on patient health and testing whether nurses are employed in the sectors with the greatest returns is important for patients, providers, and policymakers.

In this paper, we measure the effect of nurses on health care delivery and patient health outcomes using a natural experiment in Denmark, which led to a sudden and persistent 12% reduction in nurse employment. In 1994, the Danish government introduced a federally funded parental leave program, which offered parents the opportunity to take up to one year's absence per child aged 0-8. The large program take-up among women led to a substantial unintended reduction in nurse employment because nurses are a predominantly female, licensed profession with regulated training and wages that health care providers, on net, were not able to replace.

An important advantage of our empirical context is that we can combine the detailed employment data of health care providers with individual patient records on diagnoses, procedures, and health outcomes for the entire Danish population. This allows us to quantify the mechanisms through which nurses affect the delivery of care for different patient populations and to measure heterogeneous effects on patient health outcomes across different health care sectors. Comparing the returns to nursing between sectors allows us to test whether this important occupation is allocated towards sectors with the greatest returns. This is of particular relevance to policymakers, who affect the allocation of nurses to health providers through sector specific minimum nurse-to-patient ratios (Cook et al. 2010 and Lin 2014), and regulated provider prices (Hackmann 2016) or regulated nurse salaries (Propper and Van Reenen 2010). Quantifying potentially differential returns to nursing is also of growing importance as the population ages and the demand for health care services rises and a sizable proportion of the nurse workforce approaches the retirement age.

Using detailed employer-employee matched data for the years 1990-2000, we first quantify program take-up decisions for three different occupations: nurses who hold a B.Sc., nursing assistants who have completed up to 24 months of practical training, and doctors, who hold an M.D. Exploring variation in eligibility, based on the age distribution of children, we find that a large fraction of eligible nurses and nursing assistants take advantage of the

[1] http://www.bls.gov/spotlight/2015/employment-and-wages-in-healthcare-occupations/pdf/employment-and-wages-in-healthcare-occupations.pdf last accessed 12/10/16.

parental leave program. For example, the fraction of previously employed nurses with 0-1 year old children on leave increases by 15-20 percentage points following the introduction of the parental leave program. On the other hand, we find only very small take-up rates for doctors.

Despite the substantial program take up rates for both nurses and nursing assistants, the net employment effects for health care providers are very different. We find that hospitals and nursing homes, on net, are not able to replace nurses on leave, leading to a persistent 12% reduction in the stock of working nurses. We also document differential effects on net employment among health care sectors and counties, based on differences in the demographic composition of those sectors' respective workforces. This indicates that the labor market for nurses is at least partially segmented at the health sector and county levels.

This is not true for nursing assistants. We find that hospitals and nursing homes are able to fully replace nurse assistants on leave by hiring nursing assistants from other occupations and by hiring newly-trained nursing assistants. We do not see an increase in nurse assistant employment, indicating that health care providers cannot substitute nursing assistants for nurses. Therefore, we focus on nurses in the remainder of the paper.

We next exploit the exogenous variation in nurse employment at the health sector-county level to quantify the effects of nurses on the delivery of care and patient outcomes in a difference-in-differences analysis. Combining the employment data with detailed information from hospital patient records and mortality data, we find detrimental effects on hospital quality as evidenced by a persistent increase in 30-day hospital readmission rates for newborns as well as the general inpatient population. However, we find neither evidence for changes in hospital inpatient mortality nor do we detect changes in access to care.

We contrast these findings with the evidence from nursing homes where the consequences are more drastic. In the first three years following the reform, we notice a 13% increase in nursing home mortality among the elderly aged 85 and older. In absolute numbers, we find that the parental leave program reduced the number of nurses by 1,200 and raised mortality by 1,700 elderly per year. The absolute increase in mortalities is muted in the years 1998-2000, in part, because of an endogenous exit of nursing home residents who have access to outpatient long term care alternatives in the community. Taking selection into account, our findings indicate a persistent increase in the nursing home mortality rate over the entire post-reform period.

We then study the mechanisms behind these differential effects across health care sectors, through the lens of a theoretical hierarchy model of hospital and nursing home health production. A key feature of the model is that nurses have a lead role in nursing homes with only limited interactions with physicians, and hold responsibility for all residents, including the sickest. This is not true in hospitals, where in particular the most complicated cases are diagnosed and treated by doctors. Nurses assist doctors in a hierarchical structure by administering medication, monitoring and coordinating care and they have more responsibility for healthier patients. The reduction of nurses deteriorates the quality of care for different patient populations across sectors reconciling the differential mortality effects observed in the data. The model formalizes a second mechanism through which the nurse reduction may increase nursing home mortality. Nurses monitor the resident health risks and influence the discharge decision of the seemingly sickest residents to a hospital. Shortened nurse-resident interactions reduce the monitoring accuracy and thereby reduce the hospital discharge probability for the sickest nursing home residents, who may forgo more appropriate hospital treatment.

This mechanism is supported in the data by a noticeable increase in nursing home mortality caused by circulatory and respiratory diseases that could have been treated in the hospital. Furthermore, we document a reduction in the hospitalization rate among the sickest nursing home residents and provide evidence for an improvement in the risk composition of hospitalized nursing home residents. These observations are consistent with the model predictions. Comparing changes in mortality rates between hospitalized and non-hospitalized nursing home residents, we find that a substantial fraction of nursing home deaths might have been delayed, had these residents been treated in the hospital.

Finally, we investigate additional mechanisms that can reconcile the differential mortality effects between sectors. For hospitals, we detect three mechanisms that mitigate the detrimental consequences of the reduction in nurses. First, hospitals postpone the adoption of new technologies that can bind significant resources in the short term. Second, hospitals partially manage their patient mix by moving non-acute patients to less affected hospitals, which allows them to focus on local acute care patients. Third, hospitals effectively coordinate leave-taking decisions of their workforce, which allows them to avoid peak shortages, which can be particularly harmful to the patient population.

Overall, our findings indicate that nurses play a particularly important role in the delivery of nursing home care, suggesting that nursing homes are constrained in hiring nurses to meet their urgent staffing needs.

This paper makes two main contributions. First, we add to the literature on the role of nurses in the health production function. A large number of studies has investigated the effect of nurses on patient health outcomes, see Kane et al. (2007) for a review. These studies have focused on one sector at a time and relied on cross-sectional variation in nurse employment with limited attention to the endogeneity concerns regarding nurse employment. Notable exceptions are Cook et al. (2010) and Lin (2014), who exploit variation from changes in minimum nurse staffing regulations in hospitals and nursing homes, respectively. Gruber and Kleiner (2012) study the effect of nurses' strikes on patient health, using data from the State of New York, and find a large increase in in-hospital mortality for heart attack patients. Propper and Van Reenen (2010) and Stevens et al. (2015) exploit the effect of local labor market variation on nurse staffing ratios and their effects on heart attack mortalities and nursing home mortalities, respectively. Hackmann (2016) estimates a structural model of the nursing home sector in Pennsylvania using variation in Medicaid reimbursement rates and finds a marginal benefit of $126,000 of an additional nurse on staff.

Our analysis contributes to this literature in four important ways. First, we exploit a sudden, sizable, and persistent reduction in nurse employment, which allows us to assess the timing and the dynamics of changes in the delivery of care and patient health outcomes. Second, the unintended nature of our quasi-experimental variation indicates that our estimates may tell us more about the returns to nursing than aforementioned approaches. While changes in local labor market conditions and minimum staffing regulations are subject to selection on ability in the nurse workforce, the parental leave program selects by age of children and does not affect outside options of employees. Selection effects imply that business cycle variation may yield an upper bound on the marginal effect of nurses, while minimum staffing regulations may provide a lower bound. Third, we combine detailed administrative data for the entire Danish population served in different health care sectors, which allows us to quantify differences in the effect of nurses on health care delivery and patient health outcomes among health care sectors. While there is substantial mobility between the private sector and the health sector for nursing assistants, we find little evidence of such mobility for nurses. Instead, the margin between health care providers is crucial for the allocation of nurses. Fourth, we exploit data on causes of death, hospital patient records and nursing home residents to analyze the mechanisms that underpin nurses' effects on health care delivery across providers and across patient groups.

In addition to quantifying the return of a key input in the health production function, we also contribute to the literature on parental leave programs. Over the past 50 years, parental leave programs have become a prevalent and important feature of labor markets in developed countries (see Dahl et al. 2016). Previous studies have largely focused on the labor market effects for affected parents and on outcomes for children but the empirical evidence remains mixed.[2] In this paper, we argue that publicly-funded parental leave pro-

[2]On one hand, several studies find positive effects on health, educational, and earning outcomes for children (see e.g. Ruhm (2000), Rossin (2011), Carneiro et al. (2015)) and positive or only slightly negative effects on parental labor force participation (see e.g. Ruhm (1998), Waldfogel et al. (1999), Baker and Milligan (2008), and Schönberg and Ludsteck (2014)). On the other hand, other studies find no evidence for positive health or educational attainments for children (see e.g., Rasmussen (2010), Liu and Skans (2010),

grams can have significant negative externalities for employers and, ultimately, consumers if the program affects imperfectly substitutable employees in limited supply. This applies to employees who hold firm-or industry-specific human capital and occupations that require a licensed degree in particular. The specifics of the parental leave program may exaggerate the employment effects. Employers are required to guarantee the same position for the returning leave taker. Therefore, the employer may leave the position vacant if she cannot find a temporary replacement. To the best of our knowledge, we are the first to quantify this externality. We evaluate this externality in a particularly important context, given that women are more likely to take advantage of the parental leave program and that more than 97% of Danish nurses are female.

The remainder of this paper is organized as follows. Section 2 provides institutional background on nurses in health care production, the Danish health care sector, and the policy reform that we study. In Section 3 we describe our econometric approach. In Section 4, we discuss the data and we present our empirical findings in Section 5. Section 6 analyzes underlying mechanisms of the results. Finally, we conclude in Section 7.

2 Institutional Background

This section discusses the role of nurses in the health care production and describes important regulatory features of the Danish health care sector as well as the parental leave program. The goal of this section is to provide relevant background information to allow for a discussion of external validity and to motivate the empirical analysis at the regional (county) level. For additional details on the Danish health care sector see Pedersen et al. (2005).

2.1 Nurses and Health Production

As the largest group of workers in hospitals, licensed nurses have an important impact on the quality of the patient's hospital stay. Nurses monitor the patient's recovery process, identify patient needs, and catch medical errors. On the other hand, several studies indicate that patients may be over-treated at least in U.S. hospitals (Fisher et al. 2004 and Baicker and Chandra 2004) suggesting that a minor change in nurse staffing may only have minor effects on health care delivery and patient health in hospitals.

This stands in contrast to the general verdict on the quality of nursing home care which has been a notorious problem in various countries, including the US (Harrington et al.

Dustmann and Schönberg (2012), and Dahl et al. (2016)) and suggest negative net employment effects (see Dahl et al. (2016)).

2012). The quality of nursing home care hinges heavily on licensed nurses, who are primarily responsible for monitoring and coordinating the delivery of care given the limited presence of a physician in the nursing home.[3] For example, nurses provide counseling and medication, start intravenous infusions, administer oxygen, or monitor blood sugar levels for example. Nurse also provide an important input to the hospitalization decisions, see (Polniaszek et al. 2011).

This is different in hospitals, where nurses leave a bigger portion of responsibilities, diagnosis, and decision making to doctors, who ultimately have to approve the tasks carried out by nurses.[4]

2.2 The Danish Health Care Sector

Similar to other Scandinavian countries, Denmark's heath care system applies the "Beveridge" model. Health care expenses are primarily tax financed and most health care providers are publicly owned. In contrast to most other European countries, however, the Danish health care system is decentralized. For the period we study, the country was divided into 13 counties and three municipalities with county status, which are politically responsible for the financing, capacity planning and delivery of key health care services including hospitals.[5] Hospital financing is based on a system of politically fixed budgets, which provides cost control as a function of heterogeneous patient mix. The main objective of public hospitals is equal and free access to health care with a focus on professional quality and efficiency, patient safety, and satisfaction. Private hospitals account for less than 1% of the total number of hospital beds in the 1990s. Long term care services, including nursing home services, are organized at an even more granular level: the municipality level.[6] Overall, this suggests that health care systems are largely integrated at the county level.

Moreover, counties constitute separate labor markets for health care workers. 20% of nurses and 16% of nursing assistants switch jobs every year, but only 2% of assistants and 4% of nurses start a job in a different county. 88% of nurses and nursing assistants live and work in the same county and this share increases to 96% when excluding the counties related

[3]For example, less than 25% of nursing homes in Pennsylvania employ a full-time or a part-time physician between 1996 and 2000. In Denmark, general practitioners supervise the health care delivery and act as the gatekeeper for more intensive care. However, their decisions largely depend on the recommendations of nurses who outnumber doctors by a ratio of 300 compared to a ratio of only 3.3 in hospitals.

[4]Survey based evidence from the US indicates that most nurses assess their professional relationship with doctors in hospitals as collaborative but with a clear hierarchical understanding putting the doctor on top (Schmalenberg and Kramer (2009)).

[5]See Figure 17 in the Appendix.

[6]The number of municipalities was reduced from 271 in our sample period to 100 in 2007. This reform reduced the number of regions from 16 to only 5.

to the capital city.[7]

Finally, wage setting and working conditions are highly regulated in the Danish health sector, with a long tradition of cooperation between health worker unions and health care providers. Nursing assistants are members of the Danish Union of Public Employees (FOA) with almost universal membership; the Danish Council of Nurses (DNO) organizes more than 90% of nurses over the sample period. Wages depend on seniority and only differ slightly across counties and municipalities but not across health providers within geographic area. There is modest wage growth for nurses over the sample period. Real entry-level wages for nurses were increased by 3.3% in 1994 and again by 4.9% in 1998. Individual hospitals were unable to deviate from these industry agreements to attract more workers. Regulation also limits the patient responsibilities that can legally be performed by health workers other than nurses.

Our empirical analysis takes advantage of these institutional and geographic features and explores variation in the effects of the parental leave program across counties.

Our main findings, discussed below, indicate a substantial increase in nursing home mortality because of the negative nurse employment effects of the parental leave program. To put these findings into perspective, we compare elderly demographics and nursing home characteristics between Denmark and the U.S., that have similar systems for elder care in place: "provide access to nursing homes when needed, payment subsidized by tax or insurance, comparable cultural conditions, and a national system for monitoring nursing home quality", see Nakrem et al. (2009).

We provide additional details in Table 1. Both the share of elderly people in the population and the average age and share of elderly people living in nursing homes are very similar in Denmark and in the U.S. in 1993. This similarity in nursing home relevance is observed towards the end of a transition away from institutional care and towards community-based care in Denmark between 1983 and 1995. Ribbe et al. (1997) report that in 1993, there are 1,075 nursing homes in Denmark offering 39,000 beds. Their study implies that the average nursing home size in the U.S. is about twice as large as in Denmark.[8] We find an average nurse-to-resident staffing ratio in Denmark of 0.32 in 1993, which exceeds the tighter staffing ratio in the U.S. by about 28%.[9] We also compare the annual hospitalization rates of nurs-

[7]These figures are for the period 1990-1993 before the reform. We introduce the data in more detail in section 4 below.

[8]For the US, Ribbe et al. (1997) report 21,000 nursing homes and 256.6 million*12.7% elderly people. Based on the first row in Table 1, this implies 53/1000*(256.6 million *12.7%)=1.7 million beds. Hence, about 82 beds per nursing home.

[9]Based on the estimated elderly fraction in nursing homes from Table 1, we conclude that the Danish nurse staffing ratio in nursing homes equals 11,000 nurses divided by 4% of 850,000 elderly people: 11,000/(0.04*850,000)=0.32. We use data from Long Term Focus from the U.S. to construct the average

Table 1: Elderly Demographics and Nursing Homes in Denmark and the US

	Denmark	U.S.
NH beds/ per 1k elderly$^{(a)}$	48	53
Fraction elderly in nursing home$^{(a)}$	4%	5%
Fraction of population older than 65$^{(a)}$	15.4%	12.7%
Fraction of population older than 80$^{(a)}$	3.9%	2.9%
Average age in nursing home	82.2$^{(b)}$	82.2$^{(c)}$
Avg Nursing home size in beds$^{(d)}$	36.3	82
Nurse to resident ratio	0.32	0.25
Annual Hospitalization rate of NH residents$^{(e)}$	21%	30%
Doctor to Nurse Ratio in NH$^{(f)}$	0.003	0.008

Sources: (a) Ribbe et al. (1997) for the year 1993, (b) Nursing home survey for Denmark 1994, Statistics Denmark, (c) Nursing home survey for Pennsylvania, US 1996, (d) Ribbe et al. (1997) for the year 1993 and own calculations, (e) Freiman and Murtaugh (1993). (f) We compare the county average in Denmark from 1993 and Pennsylvania, US from 1996.

ing home residents, to illustrate that transitions between nursing homes and hospitals are a pervasive practice across countries. We find a slightly smaller hospitalization rate of 21% in Denmark, when compared to the estimate from Freiman and Murtaugh (1993) who use data from 1987. Finally, we find a very similar doctor to nurse ratio in nursing homes of less than 1/100 in Denmark and the US, which emphasizes the important role of nurses in the nursing home production function (when compared to doctors). In contrast, the doctor to nurse ratio equals 0.3 in Danish hospitals, which exceeds the ratio in nursing homes by a factor of 100.

2.3 Parental Leave Programs in Denmark

Denmark has a long tradition of maternity leave support going back more than 100 years, see Rasmussen (2010). After several extensions over the 1970s and 1980s, the status quo in the early 1990s was an 18-week maternity leave starting four weeks prior to birth, with full job security and generous income dependent support.[10] In addition, fathers were offered a compensated 2-week leave immediately after childbirth. Finally, parents could extend the post-birth leave time to 24 weeks, with the additional 10 weeks of parental leave to be taken by the mother or the father.

number of skilled nurse hours per resident day. Considering registered and licensed practical nurses, we find a staffing ratio of 1.44 hours per resident day. Assuming that nurses work 2,080 hours per year (52 40h weeks), we find a nurse to resident ratio of 1.44*365/2,080=0.25.

[10] The minimum of 90% of income and DKK 2,008 (about $335 in 1983-1985) per week. Most mothers received 90% of their salary, so the income effects of leave taking were relatively minor, see Rasmussen (2010).

Motivated at least in parts by high unemployment rates, the newly elected social democratic Danish government introduced several policies in 1993 that became effective in 1994 and were aimed at rotating the workforce, see Westergaard-Nielsen (2002). Most importantly, the government introduced an educational, a sabbatical, and an additional parental leave program.[11] The hope was that these programs would give unemployed people the opportunity to fill the open positions and to gain valuable work experience. The analysis in Westergaard-Nielsen (2002) suggests that the parental leave program had the largest overall impact on labor market participation, while the sabbatical and educational leave had much lower take-up rates.[12] Our approach uses eligibility rules of the parental leave program to analyze the effects of this program.

The federally funded parental leave program offers a parent the opportunity of taking up to one year of absence if the child is aged 8 or younger.[13] The program guarantees job security[14] and offers a compensation of 80% of unemployment benefits, see Jensen (2000). Unemployment benefits equal 90% of previous wages up to a maximum of \$463[15] per week, see Westergaard-Nielsen (2002). Soon after the reform, policy makers noticed that the reform led to a "bottleneck" problem in the public sector in particular, where licensed professionals could not be replaced easily (e.g., teachers and nurses). As a result, policymakers gradually cut back on the generosity of the program. Guaranteed coverage length was reduced in 1995 for children older than 1 year of age. Benefits were reduced to 70% of unemployment benefits in 1995 and subsequently to 60% in 1997 before the program was abolished in 2002, in the context of a comprehensive reform of the parental leave policies, see Pedersen et al. (2005) and Andersen and Pedersen (2007).

3 Empirical Strategy

In this section, we develop a simple empirical strategy that allows us to quantify the effects of the parental leave program on program take-up, net employment, health care delivery,

[11]In addition, transition pay for unemployed workers between the ages of 50 and 60 was offered over 1992-1995. The offer included 82% of the highest UI benefits if the worker left the labor force and went into early retirement and further reduced the available worker pool.

[12]Using data on social benefit receipts from 1995-2000, we find that these leave programs jointly account for 23 % of total paid leave time among nurses, while parental leave accounts for 77 percent, see Appendix Table 9. Moreover, a large share of education leave among nurses is due to participation in short-term continuing training, see Figure 18, and both education and sabbatical leave always require employer approval.

[13]The program guaranteed 26 weeks, see Jensen (2000). However, employees could take up to one year conditional upon employer support, see Pedersen et al. (2005).

[14]At least for publicly-employed individuals, the vast majority of individuals in our sample, see Pylkkänen and Smith (2003).

[15]DKK 2,940 at an annual average exchange rate of 6.35 DKK per USD in 1994.

and patient health outcomes. We first investigate the parental leave program take-up using variation in program eligibility across workers and over time. Second, we aggregate the take-up rates by county and health sector and investigate the effects on health outcomes in a difference-in-differences analysis.

3.1 Program Take-up at the Worker Level

We start with an analysis of parental leave program take up in year t in the sample of individuals that were employed in the previous year $t-1$. We focus on the previously employed because we can assign these health care professionals to a specific health care sector using the employer data from the previous year.

Specifically, we analyze the employment decision of parent i, whose youngest child is a years old, before and after the reform:

$$Y_{ita} = \alpha + \sum_{a=0}^{8} \alpha_a \cdot 1(ageCH_a) + \alpha_{post} \cdot Post_t + \sum_{a=0}^{8} \beta_a \cdot 1(ageCH_a) \cdot Post_t + \epsilon_{it} \ . \qquad (1)$$

Here, the dependent variable, Y_{ita}, is an indicator variable that takes the value 1 if person i is not employed in year t. $1(ageCH_a)$ refers to a series of indicator variables that take the value 1 if the youngest child is of age a. Post is an indicator variable that takes the value 1 for post-reform years. Our key parameters of interest are β_0-β_8, which indicate the take-up effects for eligible parents.

We estimate equation 1 for different sample populations. First, we separately investigate the immediate take-up effects for doctors, nurses, and nursing assistants by focusing on the sample years 1993 and 1994. In a separate set of regressions, we investigate the effects of the program in 1995 compared to 1993. These effects may be smaller, as the program became less generous over time and because parents can only once take advantage of the program for an eligible child.

3.2 Employment, Health Care Delivery and Outcomes at the County Level

To quantify the effects of the parental leave program on net employment, health care delivery, and patient health outcomes, we aggregate the estimated takeup decisions at the county-health-sector-year level. Counties define segmented health care markets as evidenced by few labor and patient movements between counties and because the financing and the coordination of health care delivery is organized at the county or even more granular levels, see Section 2.2. We also find quite different employment effects among hospitals and nursing homes in a given county, suggesting that health care markets are further segmented at the sector level. This is consistent with disconnected regulatory boards for hospital and nursing home care, which coordinate the delivery of care at the county and the municipality level, respectively.

Specifically, we cross-multiply the take-up parameters, $\beta_0, .., \beta_8$, in 1995 by the number of eligible workers in any given health sector and county in the last pre-reform year, 1993, to construct a conservative proxy for program take-up that varies among health sectors and counties. Focusing on eligible workers in the last pre-reform year provides a time-invariant measure of program take-up, which is not affected by endogenous job transitions in the post-reform years. We use the estimated take-up parameters in 1995 which are smaller than the immediate take-up probabilities and relatively stable over the following years. We refer to these as steady state take-up probabilities. Finally, we divide the product of take-up probabilities and stock of eligible nurses (predicted number of employees on parental leave) by the total number (eligible and ineligible) of employed nurses in 1993 at the county-health-sector level, and refer to this measure as "Exposure":

$$\text{Exposure}_c^s = \frac{\text{Eligible nurses}_c^s * \text{Estimated take-up parameters}}{\text{All nurses}_c^s}.$$

Similar to Finkelstein (2007) and Clemens and Gottlieb (2014), we then estimate the effect of exposure on outcomes by year as follows::

$$Y_{ct}^s = \mu_c^s + \mu_t^s + \phi * log\left(pop_{ct}\right) + \sum_{t=1990}^{2000} \lambda_t^s \cdot Exposure_c^s + u_{ct}^s \ . \tag{2}$$

Here, Y_{ct}^s denotes the respective outcome measure in county c, year t, and health sector s. We distinguish between three sectors: nursing homes, hospitals, and all other industries combined. We are primarily interested in the coefficients $\{\lambda_t^s\}$ that show the pattern of the outcome variable over time across counties with different exposure to the reform. Hence, any structural break of the λ's around the reform year 1993 will be attributed to the reform effect. We include log population as well as county fixed effects μ_c^s and year fixed effects μ_t^s as controls. This specification allows graphical inspection of potential pre-trends across counties and will guide the subsequent difference-in-difference estimation of the average reform effect on employment and mortality rates.

4 Data

An important advantage of our empirical context is that we can combine a variety of administrative data sources including employer-employee match data, patient registry data, and cause of death registers covering the entire Danish population over the period 1990-2000. We discuss these data sources in detail below.

The Danish integrated database for labor market research (IDA) covers the universe of firms and workers in Denmark over 1980-2011. The data contain information about primary employment in November each year, including plant and firm identifiers, location and industry of the establishment, and detailed worker characteristics such as gender, age, education, experience, tenure, hourly wages, and annual earnings. We add additional household characteristics such as municipality of residence, marital status, number of children, and the age of the youngest child from the population register. The latter will be particularly useful to measure eligibility of workers for the parental leave program since only parents with children aged 8 years or younger can apply for these benefits.[16]

The education variable reports the highest degree that a person has achieved from schooling, vocational training, or university education. In particular, the variable contains detailed categories of health workers that allow us to distinguish between medical doctors, nurses and nursing assistants. We define doctors as all individuals with an M.D. or Ph.D. in medicine. Nurses are defined as all individuals with a bachelor's degree or equivalent training of theory and clinical practice in nursing or midwifery, as well as nurses who completed additional specialization training as home nurses, health visitors, head nurses, nurse teachers or who participated in post-graduate training (Nursing diploma, Master in Nursing Science).[17] Finally, we define unskilled nurses or nursing assistants as social and health care aides and health care assistants with 14 months of theoretical and practical training.[18]

Next, we use industry information from the respective plant to identify hospitals and nursing homes. Our definition of nursing homes includes residential institutions for the elderly and for adults with disabilities. We summarize all other employment as the outside sector.[19] Moreover, workers without establishment affiliation in a given year are reported as

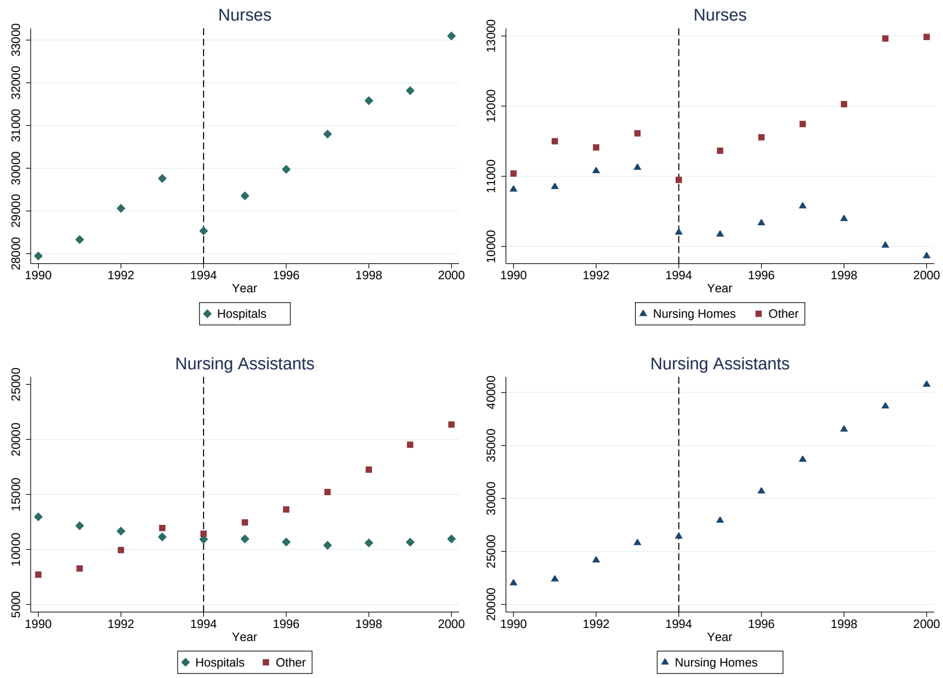
[16]From 1995, social benefits records report the beginning and end date of parental leave and other welfare receipts. We use these data to complement our annual employment indicator in November and to analyze timing and duration of leave.

[17]Nursing is a licensed profession in Denmark and only workers authorized by the National Board of Health can practice as nurses. The Act on Certified Nurses 1933 establishes "Sygeplejerske" (certified nurse) as a reserved title.

[18]The relevant professions include "Plejer", "Social- og sundhedshjaelper", "Sygehjaelper", "Plejehjemsassistent", "Social- og sundhedsassistent".

[19]There are three structural changes in industry classifications in Denmark over the time period that we study. These changes occur in 1993, 2003 and 2007. We define health sectors sufficiently broadly to be

Figure 1: Employment of Nurses and Nursing Assistants in Denmark



unemployed or non-participating. Because of the wide age range in the data, this group of individuals includes young workers in training as well as retired individuals.

Figure 1 reports aggregate trends for employment of nurses and nursing assistants in different health care sectors and the private sector over time. Nurses primarily work in hospitals; their employment share in hospitals increases over time, whereas a large and increasing share of nursing assistants work in nursing homes. The aggregate trend for nurses shows a striking drop in employment in all sectors in 1994; the drop is consistent with a labor supply shock from the leave program. In contrast, the change in employment is less pronounced for nursing assistants, where the structural break is most visible outside of hospitals and nursing homes. One interpretation of these trends is that nursing assistants in the health sector are easily substitutable from the private sector and therefore we do not observe a structural break in aggregate health care employment. Health care providers simply replace leaving nursing assistants by hiring additional nursing assistants from other occupations and by hiring newly trained nursing assistants. As a result, our analysis will mainly focus on the labor supply shock for skilled nurses.

We combine employer-employee data with information on the universe of inpatient hos-

able to provide a consistent definition of institutions over time. This prevents us from separately measuring other health care providers such as physicians, home nurses, and midwives. We rely on imputing industry information for a share of plants before 1993, but the time series of employment in different sectors do not suggest that this is a major concern.

pitalizations between 1990-2000 from the Danish National Patient Register.[20] The patient register provides information on admission and discharge dates, potential wait times, detailed diagnosis and procedure codes. We can also link the patients between the patient register, the employer-employee match data, and population registers, providing rich demographic information on the patient population. We leverage the information to measure the effect of nurses on access and quality of hospital care, e.g., the 30-day hospital readmission rate. We use the diagnosis code information to study patient subpopulations, e.g., acute care patients, and explore procedure code information to quantify the effect of nurses on technology substitution and adoption. One limitation of the diagnosis and procedure codes is that Denmark changed its classification system from ICD9 to ICD10 in 1994. We use extensive documentation sources to construct accurate time series. However, we also construct other patient populations, using additional data, that do not rely on the procedure code information, e.g. newborns.

Finally, we add mortality information from the Danish Register of Causes of Death at the person level for the years 1991-2000. The death register provides information on the death date, the cause of death, and location of death. The death location information allows us to distinguish between mortality originating from a hospital, a nursing home, and a patient's home.[21] We use this information to construct unconditional nursing home mortalities (here we do not condition on being in the nursing home). We then construct the nursing home population by matching location information for nursing homes with individual addresses from the population register. This allows us to study conditional nursing home mortalities and patient selection as well.

5 Results

In this section, we provide graphical and regression-based evidence on parental leave take-up and the subsequent effects on employment, health care delivery, and patient health.

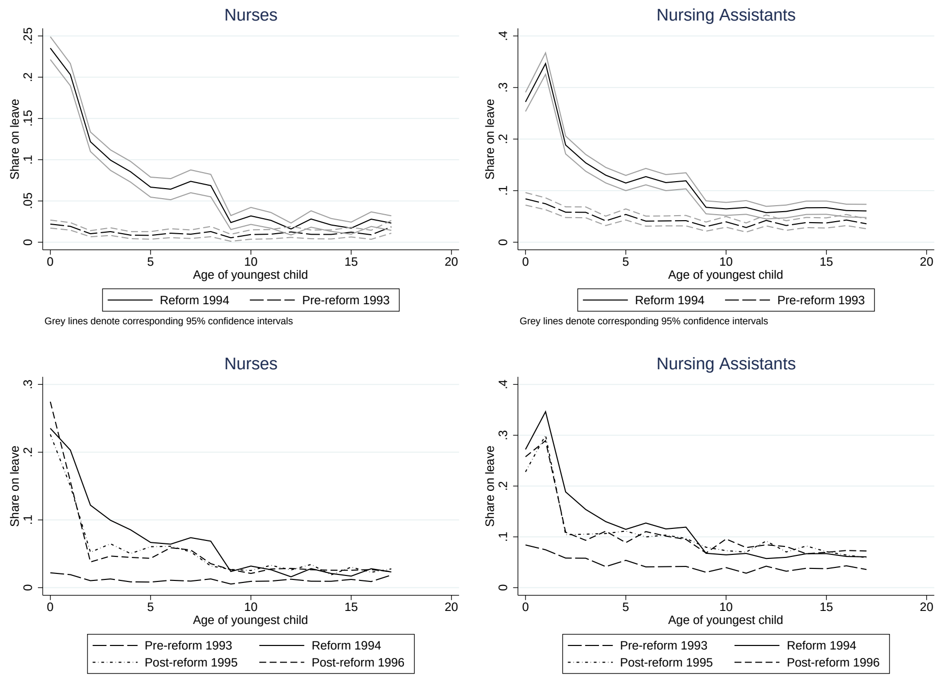
5.1 Program Participation

We first analyze the immediate take-up rates of the parental leave program. The first row of Figure 2 displays the fraction of leave takers for different health care workers by the age of their youngest child. Leave takers are defined as workers who were employed in the previous

[20] We also observe outpatient data starting in 1994. Since we require a balanced time series for the pre- and the post-reform years, we focus on inpatient data in our baseline analysis.

[21] Mortality rates in nursing homes are recorded from 1991. This is why we restrict the sample period for mortality outcomes to 1991-2000.

Figure 2: Immediate and Steady State Program Take-Up



year but are non-participating in the current year. The black dashed line documents the fraction of leavers in the pre-reform year, 1993, while the solid line shows the fraction of workers that take one year off in the first post-reform year, 1994.[22]

For both nurses and nursing assistants, we find that eligible parents, parents with a child aged 8 or younger, are much more likely to be on leave in the post-reform year in particular if they have young children aged 0 or 1. We attribute the differential effects for parents with children aged 8 or younger to the introduction of the parental leave program. Quantitatively, we interpret the vertical difference between the solid and the dashed line, relative to the difference for children aged 9 or older, as the program's take up effect. The effects are substantial. The evidence suggests that the fraction of nurses who take one year of absence increases from 3% in 1993 to about 23% in 1994, if they have a child less than one year old, see Table 10 for details. We also find evidence of bunching for children aged 6-8. This is reasonable given that this is the last chance for parents with an 8-year-old child to take advantage of the program.

The pattern is very similar for nursing assistants; here we find an increase of 16 and 24 percentage points for children in the first and second year of life, respectively. We also notice

[22] All figures pool both male and female employees. Separate analysis by gender reveals that a large share of the effect is driven by mothers, whereas fathers do not usually participate in long-term leave taking. Note that 95% of nursing assistants and 97% of nurses in the labor market are female throughout the 1990s. For doctors, the share of women steadily increases from 28% in 1990 to 36% in 2000.

a slight increase in leave taking among ineligible nursing assistants with children aged 9 or older, suggesting that nursing assistants are more likely to take advantage of the education and or sabbatical program, also introduced in 1994, which do not condition on the age of the child. Yet these changes in leave taking are small compared to the increase in leave taking for young parents. Finally, we find only very small increases in leave taking among doctors of about 2 percentage points for a child younger than one year old. There is no evidence for an increase in leave taking for older children, see Table 10 for details. Facing different career dynamics, doctors may risk potential career advancements if they take a leave of absence or they might have better access to child care facilities.

We next turn to the take-up rates in the following years to describe take-up in steady state. The immediate program take-up includes considerable bunching around the age threshold for program eligibility. We expect these initial effects to fade over subsequent years because many parents with older children have already taken advantage of the program in previous years. The second row of Figure 2 illustrates the convergence of take-up rates after the immediate surge in program participation in 1994 to what we consider "steady state" levels in the years 1995 and 1996. The left panel provides evidence for nurses and the right panel presents analogous evidence for nursing assistants respectively. Compared to immediate program take-up, the evidence suggests smaller steady-state take-up rates for parents with children aged 2 or older. We provide the analogous regression-based evidence for 1995 in column (4)-(6) of Table 10.

Overall, we find large reform effects on individual leave taking for nurses and nursing assistants. Yet health care providers are able to replace nursing assistants on leave as indicated by the smooth aggregate time trends presented in Figure 1. In contrast, Figure 1 indicates a substantial and persistent decline in nurse employment in the post-reform years. As a result, we expect the largest labor supply shock from the reform for nurses and focus our subsequent analysis on these workers.

5.2 Aggregate Effects on Employment

To reconcile the time series evidence from Figure 1 and the program take-up estimate from the previous section, we now turn to the effects of the parental leave program on net employment. Following the strategy outlined in Section 3.2, we aggregate the estimated take-up probabilities at the county and health care sector level, based on the demographic composition in 1993 and the estimated take-up parameters from 1995.

We first illustrate the statistical relationship between this reform exposure measure and immediate changes in employment after the reform in Figure 3. We compute the log change in employment by county between 1993 and 1994 for each health worker type and sector and plot these changes relative to exposure by county in 1993. There is a stronger decline in employment for counties with greater exposure to the reform. Many counties with high exposure lose more than 5% of nurses in hospitals and more than 10 % in nursing homes in the first year of the reform. The effects are even larger if we take the positive trend in nurse employment into account. On the other hand, counties with small exposure face considerably smaller reductions in nurse employment of less than 5% in nursing homes and even increases, in the case of hospitals. Overall, our conservative exposure measure can reconcile about 30.5% (13.5%) of the substantive variation in employment changes in nursing homes (hospitals) between counties. Furthermore, we find a negative correlation between employment changes in hospitals and nursing homes by county of -0.1835. This suggests that labor markets are at least partially segmented at health care sector and county level.

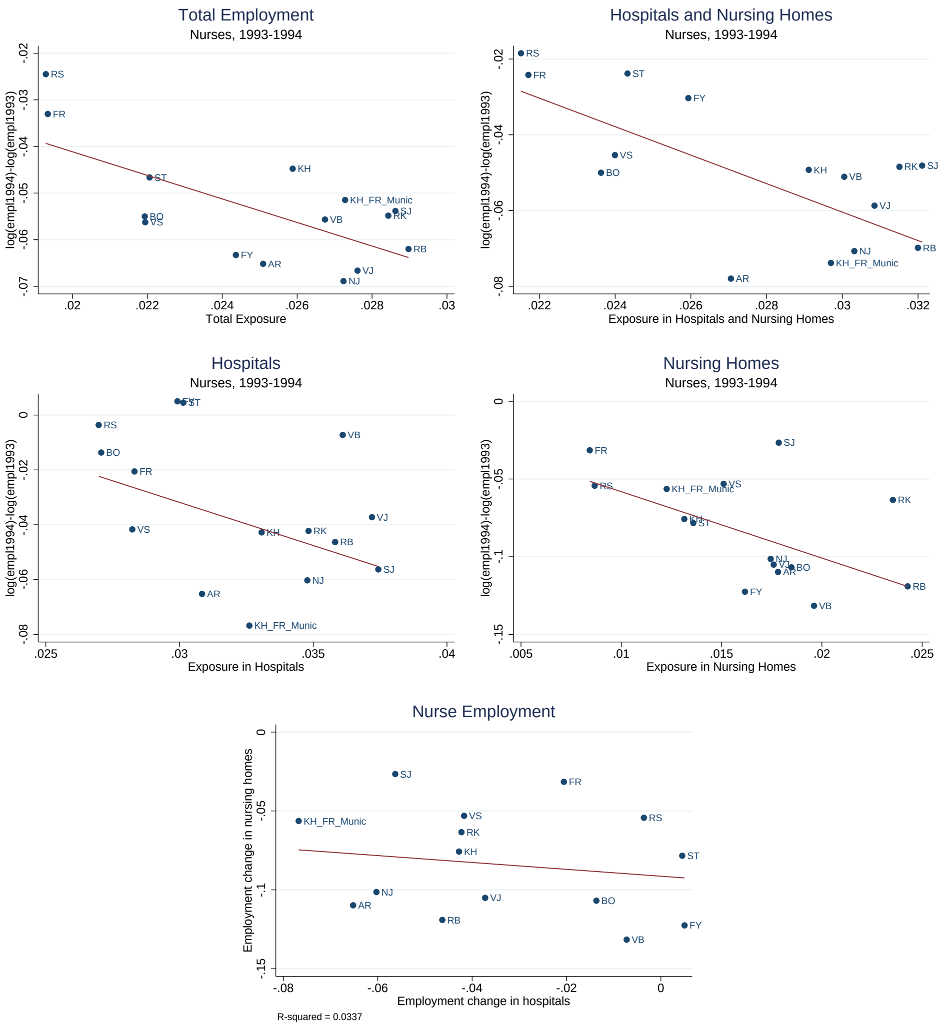
We next turn to the λ estimates of the main specification, outlined in equation (2). The first row of Figure 4 shows estimates using total employment and employment in both health sectors respectively. The second row shows employment effects of exposure separately for hospitals and nursing homes. For all specifications, there is an initial upward trend in the coefficient estimates, indicating that counties with greater exposure in 1993 grew faster in the years before the reform. This pre-trend is more pronounced at the individual health care sector level, in particular for nursing homes. All figures show a strong structural break in this growth path in 1994 when the reform starts and persistent effects in subsequent years.[23] The negative λ estimates in the post-reform years confirm the negative effect of exposure on net employment.

We report the net employment effects in Table 2. Following the structure in Figure 4, we present the effects on total employment in column 1, and columns 2-4 display more detailed effects for employment in the health care sector, hospitals, and nursing homes, respectively. The first row of Table 2 reports the average effect of exposure on aggregate employment for nurses in the post-reform years. Specifically, we estimate a difference-in-differences regression model with separate county and year fixed effects for the years 1991-1996, and report that the effect of exposure interacted with a post-reform indicator variable.[24] We also control for linear county time trends to address potential pre-trends at the county level. The point estimates suggest negative net-employment effects for total employment as well as employment in nursing homes and hospitals. To put the point estimates into

[23] All corresponding regressions are reported in Table 11 in the Appendix.

[24] We focus on a symmetric sample period with three pre- and post-reform years. We only observe nursing homes' mortality outcomes from 1991 onwards. Therefore, we omit the year 1990 (1997) to construct a consistent time window for our main findings.

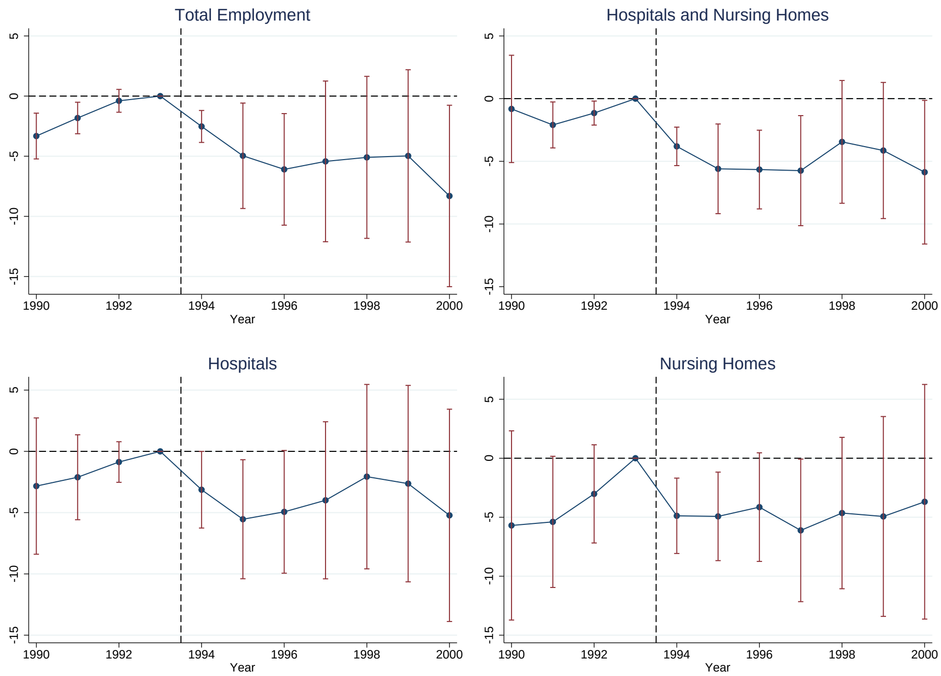
Figure 3: Reform Exposure and Employment Change 1993-1994



perspective, we quantify the average reform effect by multiplying the point estimates with the average reform exposure in the respective sector, see the last row of Table 2. The estimates suggest a net reduction in nurse employment of 13% (3,800 nurses) and 11% (1,200 nurses) in hospitals and nursing homes, respectively. This suggests that the parental leave exposure can fully account for the observed net reductions in nurse employment outlined in Figure 1.[25]

[25] Note that the point estimates for exposure are less than -1. A coefficient of minus 1 is an interesting benchmark because it indicates that nurses on parental leave reduce net employment one-to-one, suggesting that employers are, on net, unable to replace any leaver. A coefficient of less than one in absolute value would suggest that employers can at least partially replace nurses on parental leave, for example, by reactivating nurses outside the labor force. Our point estimates suggest the opposite: employment decreases by more than the number of predicted leavers. However, our exposure measure is likely to understate the amount of leave taking for several reasons. First, our take-up estimates measure the probability of leave conditional on working in the previous year and do not consider take-up among the previously unemployed. Second, based on the maximum program duration of 12 months, we implicitly assume that nurses return after one year of

Figure 4: Lambda Estimates for Employment Effects by Sector Exposure



We revisit the role of pre-trends in rows 2-4 of Table 2. Following the methodology in Finkelstein (2007), we construct deviations from pre-trends captured by the time series of lambda coefficient in Figure 4. Specifically, we construct the average effect over $\tau = 1, 2, 3$ years as follows:

$$\Delta_\tau = \frac{1}{\tau}\sum_{t=1}^{\tau}\Big[(\lambda^s_{1993+t} - \lambda^s_{1993}) - (\lambda^s_{1993} - \lambda^s_{1993-t})\Big]. \tag{3}$$

Each summand in equation (3) compares the change in trends relative to the reference year 1993 for t periods before and after the reform. This specification implies that the pre-trends would have continued at the same rate after the reform. We find significant negative effects in all specifications, both for total employment and for sectoral employment changes. Interestingly, the effects increase over time, indicating a cumulative reduction in employment that is consistent with low re-entry rates of leave takers and negative spillover effects on co-workers. The size of the average effect over three years is larger than the exposure effects for the post-reform period estimated in the first two rows, which may indicate that the assumption of persistent pre-trends in (3) provides an upper bound to the effect.

absence. However, less than 70% of nurses on parental leave return to the same county and sector within five years. If 30% of leavers do not return, the stock of leavers after five years with an equal number of leavers per year increases by a factor of 2.5. Third, we use leave taking behavior in 1995, which understates the immediate reform outcomes as shown in the first row of Figure 2. Another explanation for the large coefficients is a negative externality on co-workers, who might have to fill in the missing hours/shifts. This may encourage some co-workers to leave the employer.

Table 2: Net Employment Effects for Nurses

	(1) Total	(2) Hosp and NH	(3) Hosp	(4) NH
λ	-2.355	-4.034***	-3.952*	-6.698***
	[-5.724,1.014]	[-6.649,-1.42]	[-8.311,.407]	[-11.018,-2.378]
Δ_1	-2.918***	-4.96***	-4*	-7.904**
	[-4.65,-1.187]	[-7.288,-2.633]	[-8.266,.266]	[-15.521,-.287]
Δ_2	-6.785***	-7.696***	-7.651**	-10.325***
	[-11.922,-1.649]	[-12.246,-3.147]	[-15.283,-.019]	[-18.095,-2.555]
Δ_3	-9.416***	-6.479**	-7.768*	-9.844*
	[-14.393,-4.44]	[-12.075,-.883]	[-16.948,1.413]	[-20.489,.8]
Pre-Reform Value	52443	40886	29761	11125
Avg. Effect	-.059	-.111	-.127	-.109

The 95% confidence interval is displayed in brackets.
Standard errors are clustered at the county level. The specifications control for county and year fixed effects, log population, and linear county trends.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

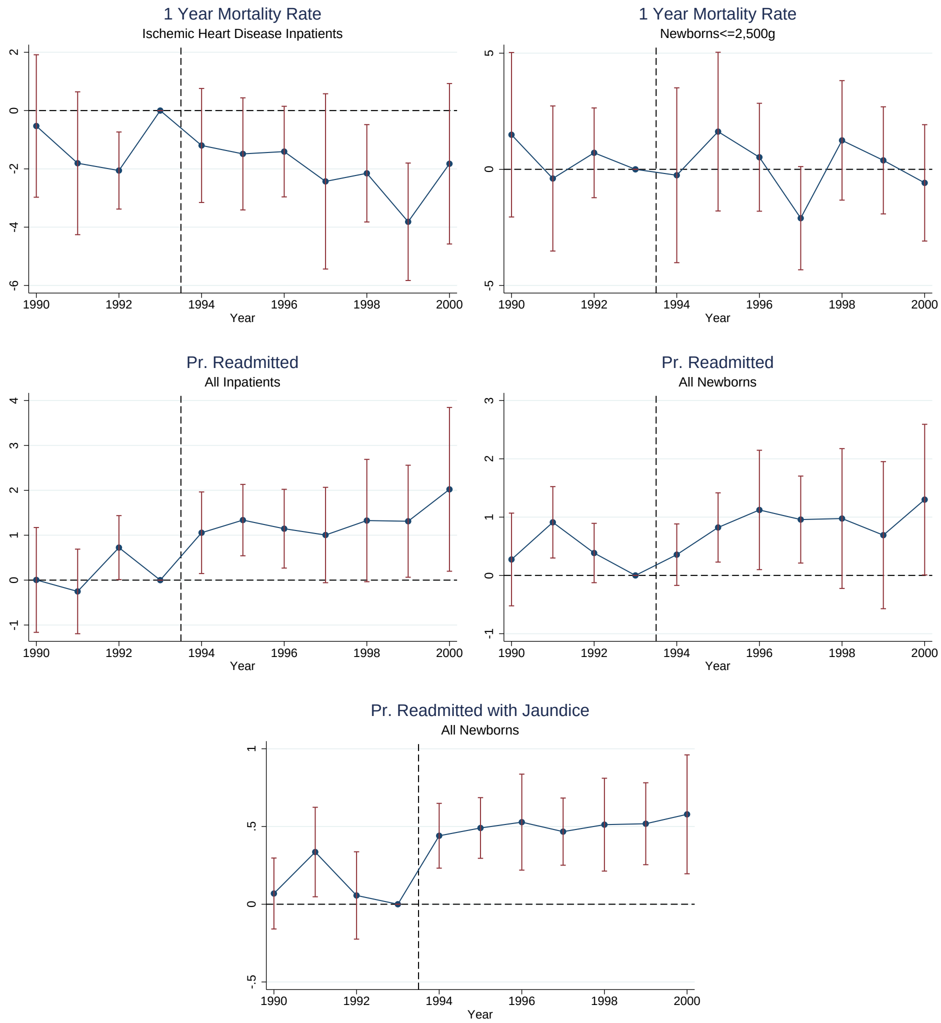
In sum, we find large effects of the parental leave program on aggregate employment of nurses, in particular in counties and subsectors with high exposure at the start.

5.3 Health Outcomes in Hospitals

Next, we turn to the effects of the net reduction in nurse employment on hospital health outcomes by exploring variation in hospital exposure between counties. We start with an analysis of hospital mortality. Confounding changes in the patient population are a canonical challenge for the identification of mortality effects. We respond in several ways. First, we link health outcomes based on the patient's county of residence, as opposed to the county of the hospital's address, to purge potential variation from hospital selection. Second, to address selection at the extensive margin (overall hospital utilization), we consider the 1-year mortality rates among acute care patients. Specifically, we follow Propper and Van Reenen (2010) and focus on heart attack patients, which we identify using detailed ICD diagnosis codes. The top left graph of Figure 5 presents the analogous λ coefficients for the one-year hospital mortality rate of heart attack patients. We find no evidence for a systematic change in the 1-year mortality rate. The corresponding average λ and Δ estimates are presented in the first column of Table 3. We repeat the analysis for inpatients whose primary diagnosis is pneumonia. We also find no evidence for a systematic change in the 1-year mortality rate.

One potentially confounding factor could be the change in the ICD classification in 1994, to the extent that differential changes in measurement across counties are also correlated with our exposure measure. In a placebo check, we find no evidence for changes in acute care visits, which provides evidence against this concern. Nevertheless, we also revisit 1-year

Figure 5: Lambda Estimates for Mortality Effects by Sector Exposure



mortality among newborns, which we observe in a different database and do not depend on the ICD classification. Specifically, we focus on babies at risk with a birth weight of less than 2,500g. We observe 44k babies at risk (about 4k per year) with an average 1-year mortality rate of 5.3%. We find no systematic evidence for changes in the 1-year mortality rate as evidenced by the top right graph of Figure 5. Finally, we also consider the unconditional annual mortality among the elderly aged 65 and older as an alternative approach to mitigate biases arising from selection at the intensive or extensive margin. Here we simply divide the overall number of deaths by the county population aged 65 and older and investigate the statistical relationship with hospital exposure. Again, we find no evidence for a change in the annual mortality rate.

Next we turn to a less drastic quality outcome measure, the 30-day hospital readmission rate, which is commonly assumed to be a signal of negative hospital quality, see e.g. the

Readmission Reduction Program (HRRP) as part of the Affordable Care Act.[26] We display the corresponding λ coefficients for the universe of inpatient visits and all newborns in the second row of Figure 5, respectively. In both figures, we see a persistent increase in readmission rates following the reduction in nurse employment in 1994, which is consistent with the persistent nurse employment effects. The corresponding average λ and Δ estimates are presented in the third and the fourth column of Table 3. The average λ effect for the three post-reform years 1994-1996 is statistically significant for both patient populations, see the first row, and implies a 21% and a 45% increase for inpatients and newborns, respectively, see the the last two rows.[27] We return to the mechanisms leading to increases in readmission rates in Section 6.

Table 3: Hospital Outcomes

	(1) Mortality Acute	(2) Mortality Newborns	(3) Readmission	(4) Readmission Newborn
λ	-.061	1.105	1.101***	.517**
	[-1.241,1.12]	[-1.096,3.306]	[.305,1.897]	[.029,1.005]
Δ_1	-1.198	-.254	1.055*	.356
	[-3.535,1.14]	[-4.753,4.244]	[-.031,2.142]	[-.274,.986]
Δ_2	-.313	.329	.834**	.397
	[-2.244,1.618]	[-3.158,3.815]	[.074,1.594]	[-.128,.923]
Δ_3	-.076	.524	1.022***	.335
	[-1.351,1.2]	[-1.723,2.771]	[.268,1.775]	[-.209,.88]
Pre-Reform Value	.241	.053	.169	.038
Avg. Effect	-.002	.036	.035	.017

The 95% confidence interval is displayed in brackets.
Standard errors are clustered at the county level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

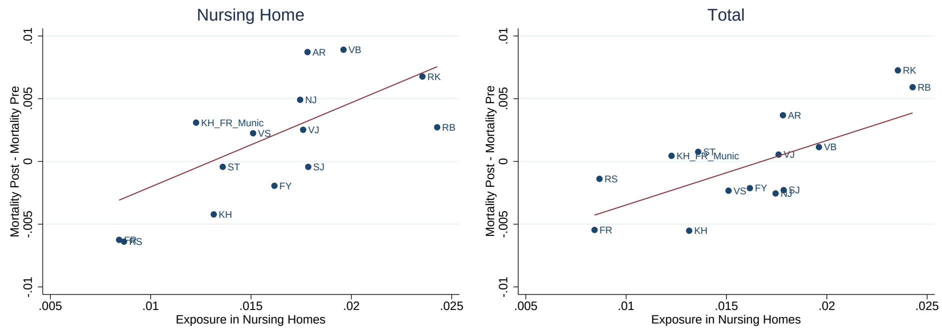
5.4 Health Outcomes in Nursing Homes

Next we turn to the effects on nursing home health outcomes using variation in nursing home exposure. We first investigate unconditional mortality rates, the overall number of mortalities in a given year, which originate from a nursing home, divided by the county population. While we do not condition on nursing home residence explicitly, we focus on the elderly population, aged 85 and older, who are likely to demand institutional nursing home care, see Table 1. We present the corresponding λ coefficients in the top left graph of Figure 7. There are no pre-trends of exposure on mortality rates, but there is a striking increase

[26]https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html, last accessed 12/26/16.

[27]The findings remain qualitatively and quantitatively almost unchanged if we control for observable patient characteristics, see Table 13 for details.

Figure 6: Mortality Effects of Nurse Shortages in Nursing Homes: Age 85 and older



in mortality rates in nursing homes in the post-reform years. The average λ estimate is statistically significant at the 1% level as indicated by the first row in the first column of Table 4. The point estimate suggests a 1 percentage point (12.8%) increase in the mortality rate, see the last two rows. To put this estimate into perspective, we multiply the mortality effect with the elderly population aged 85 and older, which equals 0.01x90,000=900. This suggests that the 12% reduction in nurse employment (about 1,200 nurses per year) increases the number of deaths by 900 elderly people per year (this increases to 1,700 if we consider the elderly aged 65 and older). The point estimate increases by only 7.5% if we further control for previous hospitalizations and age-gender fixed effects, see Table 14 for details.

We revisit differences in the mortality effects between counties in the left graph of Figure 6, where we plot the average change in nursing home mortality between the post-reform years 1994-1996 and the pre-reform years 1991-1993 on the vertical axis against nursing home exposure on the horizontal axis. Consistent with the previous evidence, we see a larger increase in nursing home mortality in counties with greater exposure in the nursing home sector. This evidence emphasizes the importance of nurses in nursing homes, and is consistent with the results in Hackmann (2016), who finds that nursing home residents highly value the number of skilled nurses per resident.[28]

We also quantify the average reform effect over $\tau = 1, 2, 3$ years as follows:

$$\Delta_\tau = \frac{1}{\tau}\sum_{t=1}^{\tau}\left[\lambda^s_{1993+t} - \lambda^s_{1994-t}\right]. \quad (4)$$

Motivated by the graphical evidence, we consider a more parsimonious specification without

[28]Using data from Pennsylvania, Hackmann (2016) estimates that residents jointly value an additional skilled nurse at about $126,000 per year. Assuming that dying residents lose only one year of the residual life time and that residents only value life expectancy, we find an upper bound on the value of the last year of a nursing home resident of about $126,000*1,200/1,700=$89,000, which is in the ballpark of estimates from the literature. Cutler et al. (1997), for example, find a "quality-adjusted-life-year" (QALY) factor of 0.62 for an 85-year-old person in 1990. This suggests a value of a year of life of about $62,000 for an 85-year-old based on a value of $100,000 in the best possible health state.

pre-trends. The point estimates are presented in rows 2-4 and are quite similar to the average lambda estimate, providing evidence for relatively constant adverse mortality effects in the years 1994-1996. However, the effects reverse back to zero in the later post reform years 1997-2000. We will return to this observation below.

Next, we consider total deaths at the county level, see the top right graph of Figure 4. Again, we see a quantitatively similar increase in mortalities in the first three post-reform years. The average λ estimate is statistically significant at the 1% level and falls short of the former estimate by only 23%, see the second column of Table 4. For a comparison of the mortality effects between counties see the right graph of Figure 6. This result emphasizes that nurse reductions in nursing homes lead to an overall increase in mortality and do not merely shift the incidence of mortality from private homes and hospitals into nursing homes. Consistent with this assessment, we find no evidence for a systematic link between nursing home exposure and hospital mortality among the elderly, see the left graph in the second row of Figure 7 and the third column of Table 4.

Table 4: Health Outcomes in Nursing Homes Among the Elderly Aged 85 and older

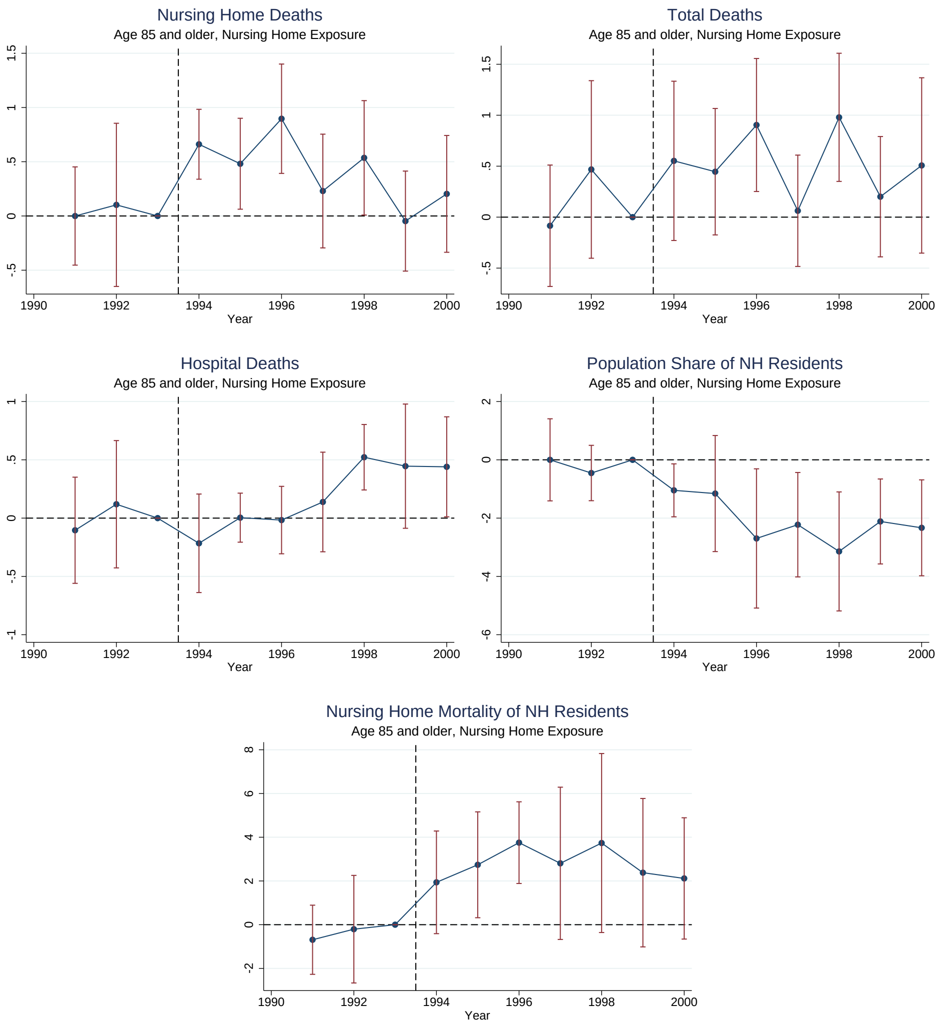
	(1) NH (uncond.)	(2) Total	(3) Hosp	(4) NH Pop Share	(5) NH (cond.)
λ	.626***	.485***	-.087	-1.738***	3.113***
	[.297,.956]	[.188,.781]	[-.439,.264]	[-3.051,-.425]	[1.619,4.607]
Δ_1	.661***	.552	-.216	-1.046*	1.937
	[.276,1.046]	[-.382,1.486]	[-.721,.289]	[-2.131,.039]	[-.869,4.743]
Δ_2	.52***	.265	-.166	-.875	2.441***
	[.151,.889]	[-.095,.625]	[-.516,.185]	[-2.715,.965]	[.724,4.159]
Δ_3	.646***	.506***	-.081	-1.482	3.108***
	[.264,1.027]	[.14,.872]	[-.451,.288]	[-3.867,.902]	[1.573,4.644]
Pre-Reform Value	.078	.16	.055	.249	.322
Avg. Effect	.01	.008	-.001	-.028	.051

Note: The dependent variable in columns (1)-(3) is mortality relative to the county population, column (4) the population share of NH residents, column (5) mortality relative to NH residents. The 95% confidence interval is displayed in brackets. Standard errors are clustered at the county level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

Finally, we return to the middle run effects on nursing home mortality for the years 1997-2000. One possibility for the reduction in the unconditional nursing home mortalities is reduced nursing home attendance. To address this possibility, we match location information for nursing homes with individual addresses to measure nursing home residents.[29] Next, we investigate the effect of nurse reduction on nursing home attendance. The right graph in the

[29]In practice, we face some limitations in the administrative data set to define nursing home addresses. At the moment we define nursing home addresses based on individuals who die in a nursing home. We will be able to refine this definition after we receive the revised address data on establishments from Denmark Statistics.

Figure 7: Health Outcomes in Nursing Homes



second row of Figure 7 shows the corresponding λ coefficients. The time series indicates an 11% reduction in nursing home attendance on average over 1994-96, see the fourth column of Table 4. A simple back-of-the-envelope calculation indicates that roughly 66% of this decrease in attendance can be explained by nursing home mortality.[30] The remaining 34% largely reflects seniors who decide to exit the nursing home in favor of alternative (potentially informal) forms of long-term care support. We will come back to this point in the the mechanism section.

Taking the change in nursing home attendance into account, we also investigate the conditional mortality rate among nursing residents, see the bottom graph of Figure 7. We

[30] If mortality in nursing homes increases by 5.2%, on average, over 1994-96, and initially 24.9% of elderly age 85 and older live in a nursing home, this NH share decreases to 22.1% after three years if mortality outside of nursing homes remains unchanged.

now see a smaller reduction in the mortality rate after 1996, which suggests persistent adverse mortality effects even 7 years after the introduction of the parental leave program. The corresponding point estimates are summarized in the fifth column of Table 4.

6 Mechanisms

In this section, we provide details on mechanisms that can reconcile differential effects on health care delivery and patient health between hospitals and nursing homes. We first present a theoretical model of hospitals and nursing homes and evaluate its testable predictions in the following subsections. Finally, we turn to additional mechanisms that can mitigate the effects of nurse reductions on patient health in hospitals.

6.1 Theory: A Model of Hospitals and Nursing Homes

Patients A health care sector k is characterized by a fixed mass of patients M^k who differ in their patient risk type s, representing the severity of their illness or difficulty of treatment. For simplicity, let $s \in \{n, r\}$ with normal patients n and high risk patients r. We assume a probability distribution across patient types that is specific to a health care sector, with population share p^k of risky patients in sector k. In particular, we distinguish hospitals *hosp* and nursing homes *nh* with $p^{hosp} > p^{nh}$.

Health Care Workers The production at health care providers requires two tasks: diagnosis and treatment. Health workers provide a fixed unit of time as labor supply and they allocate their time across these two tasks and across different patients. Providers can hire two different types of workers for these tasks who differ in their ability to diagnose and treat patients: nurses and doctors.

Diagnosis follows a top-down approach. The most skilled workers are responsible for diagnosis and delegate certain patient-related tasks to lower hierarchy levels if available. However, doctors and nurses differ in their expertise with respect to patient diagnosis. In particular, for every unit of time that a doctor spends with a patient, she extracts a more precise signal of patient health than a nurse could. For simplicity, we assume that doctors perfectly recognize a patient's health status with a fixed time input $\bar{d}$, whereas nurses only receive a noisy signal

$$v \sim G(s, \sigma(d))$$

with mean at the true health status s and variance $\sigma(d)$ decreasing in the diagnosis time d spent with the patient.

Treatment occurs in the remaining time of health care professionals. Doctors have an absolute advantage in treatment over nurses for all patients. Yet in the presence of doctors, nurses are also more effective in treating high risk patients. Nurses can assist doctors in the operating room using complementary capital to have a larger impact on patient health. Without doctors, nurses treat all patients more similarly by providing monitoring, counseling and medication for example. These assumptions follow the highly regulated health care system with respect to patient-related tasks as reflected by education, training and occupational licensing among health care workers.

Patient Health Outcomes The survival probability of patients is a function of a patient's current risk type s and treatment time from doctors t_{doc} and from nurses t_{nurse},

$$y = f(s, t_{doc}, t_{nurse})$$

which is the main objective of health care providers. We make the following assumptions about the health production function:

(A1) For given time input, health outcomes are worse for riskier patients, $f_s < 0$.

(A2) For given risk type, health outcomes improve in time investment, $f_t > 0$, with diminishing returns, $f_{tt} < 0$.

(A3) Without doctors, the marginal value of nursing time is equal across patients, $f_{st,nurse} = 0$. If doctors are present, nursing time has a larger impact on sicker patients, $f_{st,nurse} > 0$, and returns diminish more quickly for sicker patients, $f_{stt,nurse} < 0$, i.e. the treatment function has more curvature.

(A4) For any patient, treatment time from doctors is more valuable than from nurses, $f_{t,doc} > f_{t,nurse}$, but doctors have a comparative advantage in treating high risk patients, $f_{st,doc} > f_{st,nurse} \geq 0$.

Organization of Health Production and the Provider's Problem Providers face a basic tradeoff: Hiring doctors can be considered a fixed cost that may be associated with additional investment in capital and equipment as well. However, doctors improve the precision of diagnosis and the subsequent allocation of treatment time across patient risk types, and they provide better treatment especially to high risk patients under (A4).

For this discussion, we assume that hospitals are willing to pay this fixed cost because they treat more high risk patients. First, there is a larger share of high risk patients in hospitals that need adequate treatment to prevent death. Second, hospitals treat a larger number of patients such that doctors can leverage their skills across a larger number of patients.

A provider (sector) k maximizes patient health by choosing the task allocation across health care workers conditional on organizational structure and on the patient population M^k. In particular, hospitals solve

$$\max_{\{t_{n,h},t_{r,h}\}_{h\in nurse,doc}} \sum_{m\in M^{hosp}} f^{hosp}\left(s_m, t_{s,doc}, t_{s,nurse}\right)$$
$$\text{s.t.} M^{hosp}\left[\left(1-p^{hosp}\right)t_{n,doc}+p^{hosp}t_{r,doc}\right] = N_{doc}T - M^{hosp}\bar{d}$$
$$M^{hosp}\left[\left(1-p^{hosp}\right)t_{n,nurse}+p^{hosp}t_{r,nurse}\right] = N_{nurse}T.$$

The assumptions of fixed diagnosis time from doctors and full information about patient risk type mean that the allocation of treatment time can be specified according to true health status.

This is not true in nursing homes, where the diagnosis from nurses leaves some (more) uncertainty about the true risk type of a patient. For simplicity we model nurse visits to patients as combining patient treatment and monitoring.[31] Instead of hiring doctors, nurses in nursing homes have the option to transfer patients to a hospital at a fixed cost c. We interpret c as the expected increase in mortality from the transport to the hospital for any patient.[32] High risk patients benefit differentially from hospital care. In contrast, if a normal patient is transferred to a hospital, they will be diagnosed and then sent back to the nursing home.[33]

We nest the hospitalization decision into the nursing home objective function in a tractable way by imposing the following timing structure. First, nursing homes choose the nurse time spent per resident t_{nurse}, which has an immediate impact on resident health captured by a health transition matrix $Pr(s \to s') = p(t_{nurse}, s)$. Second, nurses receive a noisy signal v as a function of new health status s' and diagnosis time $d = t_{nurse}$, which informs the hospital discharge decision. Finally, mortality is determined based on health status s' and follow-up treatment in the hospital or nursing home described by function $f(\cdot)$.[34]

[31] This simplification emphasizes the relationship between screening time and hospitalizations. We can easily relax this assumption to allow for separate diagnosis and treatment time of nurses and adjustment in time allocation across these tasks, see the comments below.

[32] This increase could be directly related to the transfer or result from financial costs of hospitalizations that divert nursing home funds from patient care, see Castle and Mor (1996).

[33] The hospital faces a capacity constraint and does not provide care to normal patients who can be treated in nursing homes. Other normal hospital patients do not have access to these other sources of care. This assumption can easily be made explicit in a model with heterogeneous patient types across hospitals and nursing homes at the cost of additional notation.

[34] The pre-hospitalization treatment in nursing homes allows for the possibility that negative nursing home

The nursing home chooses nurse time per residents and hospital transfers, $Tr(v, t_{nurse}) \in \{0,1\}$, optimally to maximize patient health:

$$\begin{aligned}
\max_{t_{nurse}, Tr(\cdot)} \sum_{m \in M^{nh}} & \Big[1 - Tr(v_m, t_{nurse})\Big] f^{nh}\left(s'_m, t_{nurse}\right) \\
& + Tr(v_m, t_{nurse}) * 1\{s'_m = r\} \cdot \left[f^{hosp}\left(r\ , t^{hosp}_{r,doc}, t^{hosp}_{r,nurse}\right) - c\right] \\
& + Tr(v_m, t_{nurse}) * 1\{s'_m = n\} \cdot \left[f^{nh}\left(n, t_{nurse}\right) - c\right] \\
\text{s.t.} M^{nh} t_{nurse} = & N_{nurse} T,
\end{aligned}$$

where $1\{\}$ is an indicator variable that turns on if the event is true. We simplify the resource constraint in nursing homes by ignoring capacity incentives of hospitalizations. This seems plausible because of ethical considerations and the goal of these public providers to grant full access to health care for the population.

Closing the model Note that despite these differences in nursing tasks across hospitals and nursing homes, wage regulation prevents competition for workers across providers. We assume that the supply of nurses and doctors by sector is exogenous and we consider allocation of tasks within each sector conditional on available resources. For policy analysis, one could think about wage interventions that change the relative supply of nurses across sectors.

Model Implications

We next characterize the main implications of the model. All proofs can be found in the Appendix.

Lemma 1: Time Allocation *Under assumptions (A1)-(A3), health workers in hospitals optimally spend more time treating riskier patients, $t_n < t_r$. Nurses in nursing homes spend the same amount of time $t = \frac{NT}{M}$ on all patients.*

Proposition 1: Hospital Patients *Under assumptions (1)-(3) and $f_{ttt} \leq 0$, if the number of patients per nurse in hospitals increases, the time spent on a regular patient decreases more than the time spent on a risky patient. Health outcomes for regular patients deteriorate more than health outcomes for risky patients.*

treatment affects health outcomes among hospitalized residents, ignoring the selection effect.

Intuitively, this result shows that the regular hospital patient is the marginal patient whose health care inputs are more sensitive to staffing supply shocks than inputs for sicker patients. This result suggests that patients with moderate health risks suffer the largest adverse effects in hospitals, while health effects for sick patients will be small.

Lemma 2: Hospitalization Cutoff *The nursing home chooses a cutoff signal v^* above which a patient will be transferred to a hospital.*

The signal cutoff for hospitalizations sets the marginal cost of hospitalizations, c, equal to the marginal benefit, given by the health advantage from hospital treatment for a high risk patient, Δy, weighted by the probability of discharging a sick patient at the margin v^* expressed as the ratio of probability densities at the cutoff,[35]

$$c = \frac{p^{nh} \cdot g_r(v^*)}{p^{nh} \cdot g_r(v^*) + \left(1 - p^{nh}\right) \cdot g_n(v^*)} \cdot \underbrace{\left[f^{hosp}\left(r, t^{hosp}_{r,doc}, t^{hosp}_{r,nurse}\right) - f^{nh}(r, t_{nurse})\right]}_{\Delta y}. \tag{5}$$

If the cost is sufficiently high and the share of high risk patients sufficiently low, the cutoff will lie strictly above the median signal for healthy patients, $v^* > n$. This condition holds in the data because we only observe about 21% of nursing home patients being discharged to a hospital per year.

Proposition 2: Nursing Home Residents *A decrease in nurse staffing in nursing homes leads to the following predictions about nursing home patients:*

1) Lower treatment time per patient leads to a deterioration of health status for all nursing home patients (care effect).

2) Lower diagnosis time per patient reduces signal quality and increases the share of high risk patients who remain in the nursing home instead of receiving adequate care in a hospital (screening effect).

3) With less time per patient, total hospitalizations and patient risk mix among hospital transfers increase through the care effect and decrease through the screening effect.

4) If total hospitalizations remain unchanged after a decrease in the time per patient, an improvement in patient risk among hospital transfers suggests that the elasticity of screening quality with respect to nurse-patient time is higher than the elasticity of patient risk type.

Hospitalization is costly and the information content of the signal has decreased as nurses spent less time with each patient. Hence, a stronger signal is required to trigger hospital-

[35] Here p^{nh} denotes the fraction of risky residents based on the interim health profile s' but before hospitalization.

ization. As a consequence, a larger share of high risk patients will forego necessary hospital treatment and is exposed to higher mortality risk. Overall, hospitalizations will decrease as the signal becomes noisier to prevent unnecessary transfers. At the same time, conditional on hospitalization, the patient mix becomes more positively selected as the share of high risk patients decreases.

The counteracting force is an overall reduction in patient health among nursing home residents through the "care effect". If there are more sick patients overall, hospitalization becomes more attractive for the average resident and the nursing home has an incentive to increase total hospitalizations. A deterioration in overall patient health will also negatively affect the patient mix of hospital discharges, counteracting the positive selection from noisier signals. The overall outcome for hospitalizations and risk profiles of hospitalized residents will depend on the relative strength of care and screening effects.

6.2 Evidence from Hospitals

The previous evidence from Section 5.3 indicates a significant increase in the 30-day hospital readmission rate for different patient populations following the reduction in nurse employment. However, we find no evidence for an increase in hospital mortality rates. These findings are consistent with the predictions from the theoretical model, see Proposition 1, which suggests relatively minor adverse consequences for the sickest patients as doctors, who are not affected by the parental leave program, can still adequately diagnose and allocate treatment resources towards the sickest patients. Hence, the adverse consequences of nurse reductions are largely borne by healthier patients as evidenced by the increased readmission rates.

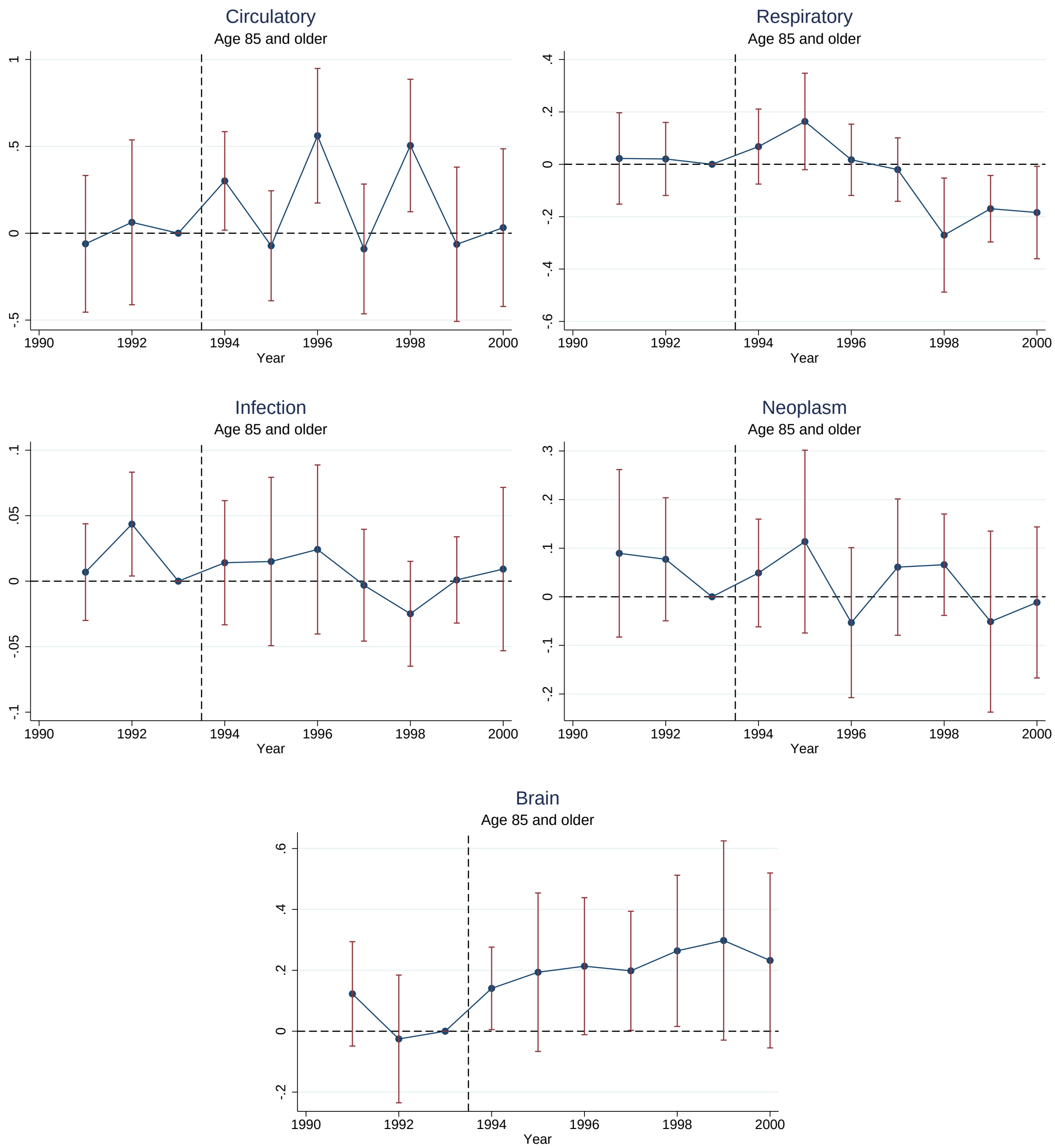
To provide more details on the underlying mechanisms leading to increased readmission rates, we revisit the previous evidence within a more narrowly defined and homogeneous sub-population among newborns. Specifically, we focus on neonatal jaundice, which is the most common primary diagnosis among readmitted babies, and a driving force behind the observed increase in 30-day hospital readmissions among newborns, see the the last row of Figure 5. Neonatal jaundice (yellowing of the skin) is a common and typically harmless condition among newborns and a result of elevated bilirubin levels, see Maimburg et al. (2010) for details. However, exposure to high serum bilirubin levels, hyperbilirubinemia, is neurotoxic and can lead to severe brain damage or even death. One mechanism that can tie the decrease in nurses on hospital staff to increased newborn readmissions for jaundice is that the reduced nurse patient time deteriorates the nurse's ability to detect symptoms that are indicative of high bilibrium levels, thereby increasing the number of falsely discharged newborns (Ebbesen 2000). While we cannot measure nurse-patient time directly, we can test for changes in the babies' length of stay in the hospital stay related to birth. However, we find no evidence for a decrease in the length of stay among newborns in general and newborns at risk (birthweight above 2,500g) who are more likely to develop jaundice.

Finally, we turn to the severity of the underlying causes leading to increased readmissions, which is relevant for a comparison of the returns to nursing between hospitals and nursing homes. Specifically, we test for negative long-term effects on the newborns cognitive skills given that high serum bilirubin levels are neurotoxic. One severe but also rare type of brain damage, which may be caused by high serum bilirubin levels exposure, is kernicterus. According to Ebbesen (2000) there have not been any cases of kernicterus in Denmark in the 20 years leading up to 1994. Between 1994 and 1998, however, six cases were diagnosed providing first evidence for a potentially harmful and long-lasting effect of the nurse reduction on newborn health. While we cannot track these individuals in our sample population, we follow Maimburg et al. (2010) and test for an increase in autism and mental disorders, which may also be caused by high serum bilirubin levels. To this end, we track newborns between the age of 3 and 17 and test for an increase in hospital admissions whose primary diagnosis is either autism or a mental disorder more generally. However, we do not find conclusive evidence for systematic changes in the prevalence of autism or mental disorders. Therefore, we cannot conclude that the increase in readmissions has a persistent negative effect on newborn health.

6.3 Evidence from Nursing Homes

The first prediction from Proposition 2 postulates adverse health outcomes for all nursing home residents. For example, the reduced number of nurses on staff may reduce the quality of resident monitoring, which may increase the response time to emergencies but may also reduce the ability to detect and treat health conditions at an early stage (e.g., a respiratory infection), thereby affecting relatively sick as well as relatively healthy residents. To tie this prediction more directly to the empirical evidence, we first decompose the large mortality effects outlined in Section 5.4 by cause of death, leveraging detailed information from the cause of death register. We distinguish between cardiovascular and respiratory causes, infections, cancer, and causes related to degenerative brain diseases, see Figure 8 for the graphical evidence and Table 5 for the corresponding regression results. We find that the increase in nursing home mortality rates is mainly driven by cardiovascular diseases, brain diseases, and respiratory diseases. These three categories account for 70 percent of the overall increase in mortality among the elderly aged 85 and older. Brain diseases include dementia and senility and are most common among the oldest and weakest residents in nursing homes, suggesting a disproportionately large mortality effect for this group. However, the effect on cardiovascular related mortality is twice as large and may include healthier residents as well. Overall, this suggests substantial increases in mortality among healthy and sick residents, which is consistent with the predictions from the theoretical model.[36]

Figure 8: Lambda Estimates for Mortality Effects by Cause of Death in Nursing Homes



[36]Finally, we find very similar effects regarding the cause of death when considering overall mortality at the county level. This suggests again that the increase in nursing home mortality does not primarily reflect patient reallocation between hospitals and nursing homes. The corresponding tables and figures are available upon request.

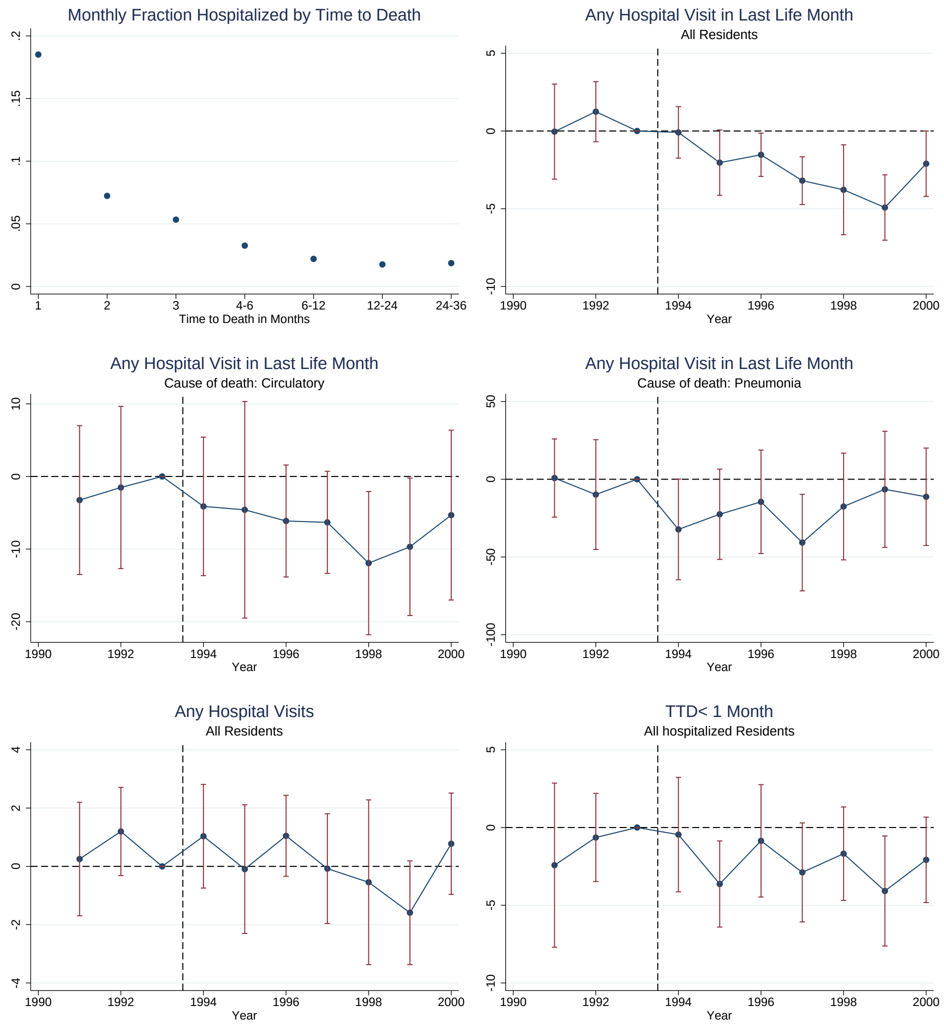
Table 5: Mortality Effects by Cause of Death in Nursing Homes: Age 85 and older

	(1) All	(2) Cir	(3) Neop	(4) Inf	(5) Res	(6) Bra
λ^{post}	.626***	.256***	-.023	0	.074	.145**
	[.297,.956]	[.097,.415]	[-.15,.104]	[-.049,.05]	[-.047,.194]	[.016,.274]
Δ_1	.661***	.301*	.049	.014	.068	.141*
	[.276,1.046]	[-.038,.64]	[-.083,.181]	[-.043,.071]	[-.104,.239]	[-.021,.303]
Δ_2	.52***	.083	.043	-.007	.105*	.18***
	[.151,.889]	[-.177,.343]	[-.084,.169]	[-.069,.055]	[-.008,.219]	[.05,.31]
Δ_3	.646***	.263***	-.019	.001	.069	.15*
	[.264,1.027]	[.092,.434]	[-.166,.128]	[-.052,.053]	[-.076,.213]	[-.006,.306]
Pre-Reform Value	.078	.046	.007	0	.008	.007
Avg. Effect	.01	.004	0	0	.001	.002

Causes of death are: Cir-Circulatory, Neop-Neoplasms, Inf-Infections, Res-Respiratory, Bra-brain diseases. The 95% confidence interval is displayed in brackets. Standard errors are clustered at the county level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

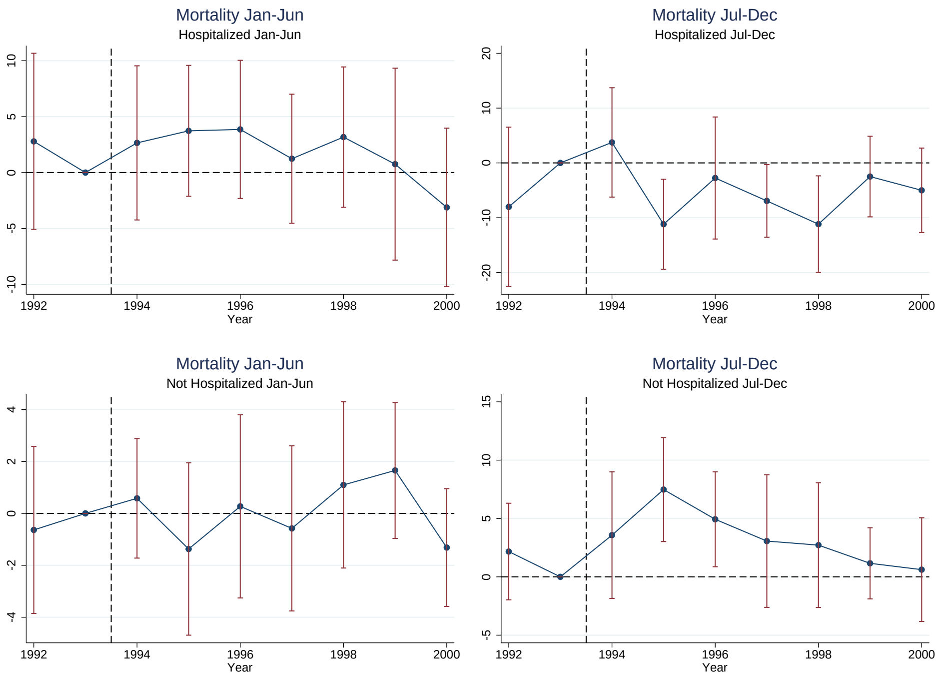
Next, we test the theoretical predictions regarding the hospitalization rates of nursing home residents. The increase in cardiovascular and respiratory mortality raises the concern that some residents forgo more appropriate treatment in hospitals. One possible explanation, formalized in the theoretical model, is that the reduced nurse-patient time reduces the ability of nurses to diagnose acute resident conditions that should be treated in the hospital. Specifically, the second prediction of Proposition 2 postulates a decrease in the hospitalization rate among sick residents, whereas a model without screening would suggest an increase hospitalization rates, see the third prediction of Proposition 2. To test the screening mechanism, we characterize the risk type of a resident by the remaining life expectancy, measured by the time to death. Precisely, we focus on very sick residents with a residual life expectancy of less than one month, who have disproportionately high hospitalization rates as indicated in the top left graph of Figure 9. We also conduct separate analyses for the subgroup of residents whose cause of death is either related to a circulatory disease or pneumonia. We choose these specific resident populations for three reasons. First, these conditions are primarily treated in a hospital. Second, we can track these populations consistently over time despite classification changes in ICD codes. And third, we see evidence for increased mortality among these patient groups. The top right graph and the graphs in the second row in Figure 9 show the corresponding λ coefficients for hospitalization rates in the last month before death. Overall, we see a statistically significant decrease in the post-reform years in each sample population, suggesting that the reduction of nurses in nursing homes decreases important access to hospitals among residents with high mortality risks, see columns 2-4 from Table 15 for details. This confirms the second prediction of Proposition 2 and the crucial role of patient monitoring in nursing homes.

Figure 9: Hospitalizations of Nursing Home Patients



We analyze the overall hospitalization rate in the bottom left graph but find no evidence for a systematic change in hospitalizations. From the perspective of the theoretical model, this suggests that the incentives for hospitalization stemming from a reduction in the signal precision and the reduction in resident health cancel out on average, see the third prediction of Proposition 2. Next, we turn to the risk selection of hospitalized nursing home residents. To this end, we construct the one-month mortality rate among hospitalized residents and test for systematic changes in the risk composition following the introduction of the parental leave program. The λ coefficients from the bottom right graph in Figure 9 indicate that the nurse reduction in nursing home leads to a positive selection of hospitalized nursing home residents, see column 5 of Table 15 for the respective point estimates. Considered through the lens of the model, this suggests that the effect of reduced signal precision dominates the negative treatment effect with respect to patient selection for hospital transfer. With less information

Figure 10: Hospitalizations and Nursing Home Mortality



about true health status, the nursing home accidentally transfers more healthy patients although their share in the total resident population has declined. This dominant effect of screening results in an unintended positive selection in hospitalized residents, consistent with the fourth prediction of Proposition 2.

Finally, we return to the congruent increase in nursing home mortality and the reduction in hospitalizations conditional on patient risk. Specifically, we investigate whether hospitalizations simply prevent the elderly from negative nursing home exposure and thereby raise life expectancy. Alternatively, hospitals may address the patient complications and thereby undo the negative nursing home exposure. To distinguish between these alternative mechanisms, we exploit variation in nursing home exposure and hospitalizations between residents. Specifically, we focus on newly admitted residents only and distinguish between residents that spent more or less than 6 months in the nursing home and were or were not discharged to a hospital. The left graphs from Figure 10 contrast the mortality rate over the first two quarters between residents that were discharged to a hospital (first row) and residents that were not (second row). We find no evidence for a significant change in mortality, see Table 16 for details. This suggests that nursing home exposure of less than 6 months has no effect on mortality.

We build on this finding in the second column, where we compare elderly individuals who spent the first two quarters of the year in the nursing home but were (were not) discharged to a hospital in the second half of the year. The evidence from the first column suggests that both populations were roughly equally exposed to negative nursing home exposure, given that extra treatments of less than 6 months have no significant impact on the 6 month mortality rate. Despite comparable nursing home exposure, we find quite different effects on mortality. On the one hand, we find a statistically significant increase in mortality among residents who are not discharged to a hospital, bottom right graph. On the other hand, we find no statistically significant effect on mortality for residents who were discharged to a hospital, top right graph. Ignoring patient selection, this suggests that hospitals can at least partially undo the negative consequences of adverse nursing home exposure. Overall, these findings are consistent with a negative effect of nursing home exposure on mortality as evidenced in the bottom right graph. Ignoring selection, the evidence also suggests that the mortality increase could have been reduced had high risk nursing home residents had access to hospital care, emphasizing the important role of hospital discharges as a mechanism to improve patient health. We notice that advantageous risk selection in hospitals can mask potentially negative mortality effects, if the amount of selection increases with nursing home treatment. Therefore, we interpret the findings displayed in Figure 10 as suggestive evidence for an important link between hospitalizations and mortality.

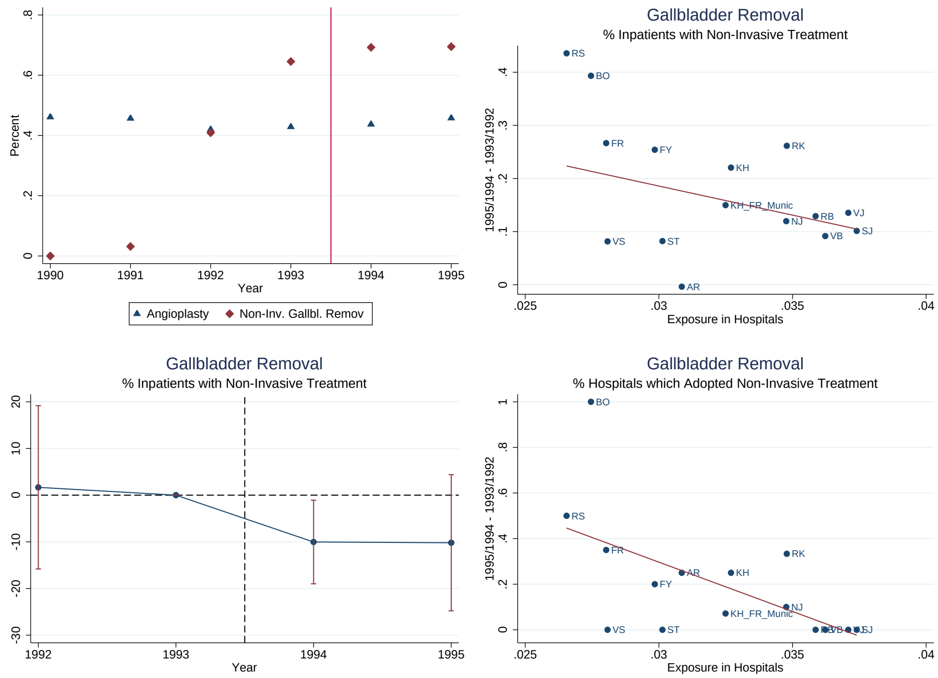
6.4 Other Mechanisms

6.4.1 Technology Adoption and Substitution in Hospitals

An additional mechanism, not captured in the theoretical model, that can reconcile differential effects of nurse reduction on patient health between nursing homes and hospitals is the role of technology adoption and substitution. Specifically, hospitals may substitute technologies that share fewer complementarities with nurses and to postpone the adoption of new technologies that can bind significant resources in the short term in order to mitigate the adverse consequences of nurse reductions. We investigate these hypotheses in the context of two conditions that each allow for a traditional invasive surgical treatment option and a technology-intense non-invasive treatment option.

The first treatment decision applies to patients whose blood flow is compromised or even completely blocked due to built-up plague inside coronary arteries. The invasive treatment option is to connect a healthy artery or vein to the blocked artery to bypass the blocked part of the coronary artery, commonly referred to as a Coronary Artery Bypass Graft (CABG). The non-invasive angioplastic treatment option is to introduce a collapsed balloon to the artery and move it via a catheter to the clogged portion of the coronary artery, where it is inflated to widen the artery. Both treatments are applied at similar frequency in our sample

Figure 11: Technology Substitution and Adoption



population, as indicated by the top left graph of Figure 11. The blue triangles indicate the annual share of non-invasive angioplasty relative to the total number of invasive and non-invasive treatments. Using the detailed procedure code information from the National Patient Register for the years 1990-1995, we investigate whether hospitals with a larger decline in their nurse workforce are more likely to substitute the non-invasive angioplastic treatment option. However, we find no evidence to support this hypothesis, see the online appendix for details.

The second treatment is applied to patients who develop gallstones, which can irritate the gallbladder and thereby induce intense tummy pain. The invasive treatment (open cholecystectomy) requires a larger incision to the tummy in order to access and remove the gallbladder. The non-invasive treatment option (laparoscopic cholecystectomy) requires only very small cuts, as fine surgical instruments are used to remove the gallbladder. The latter treatment option was effectively non-existent in 1990 and 1991, as indicated in the top left graph of Figure 11, which again measures the ratio of the non-invasive over both treatment options on the vertical axis. Hospitals started to adopt this technology in 1992 and it gained a market share of almost 70% by 1995. We test whether hospitals with the largest reductions in nurse employment delay the adoption of this new technology in the top right graph of Figure 11. Here, we plot the change in the fraction of laparoscopic treatments against the exposure in hospitals. The negative slope supports our hypothesis, indicating smaller increases in laparoscopic treatments in counties with the largest reductions in nurse employment. The left graph in the second row plots the corresponding λ coefficients for the two relevant pre- and post-reform years 1992-1995. The significant decline in the λ coefficients in 1994 further corroborates the negative effect of hospital exposure on technology adoption.

The presented patterns combine adjustments along the intensive margin, the number of patients being treated, as well as the extensive margin, any patient being treated. To decompose this pattern, we analyze the extensive margin separately in the bottom right graph of Figure 11. Here, we measure the fraction of hospitals in the county that have adopted the non-invasive technology as indicated by treating at least one patient in the given year. To address potential specialization of hospitals, we restrict the analysis to hospitals that treat at least one patient with either the invasive or the non-invasive procedure in each year of our sample period. Next, we construct averages in the pre- and post-reform period and plot the change for each county on the vertical axis of the bottom left graph of Figure 11. We find a clear negative pattern, suggesting that hospitals are less likely to adopt the non-invasive technology in counties with higher hospital exposure.[37]

6.4.2 Patient Management

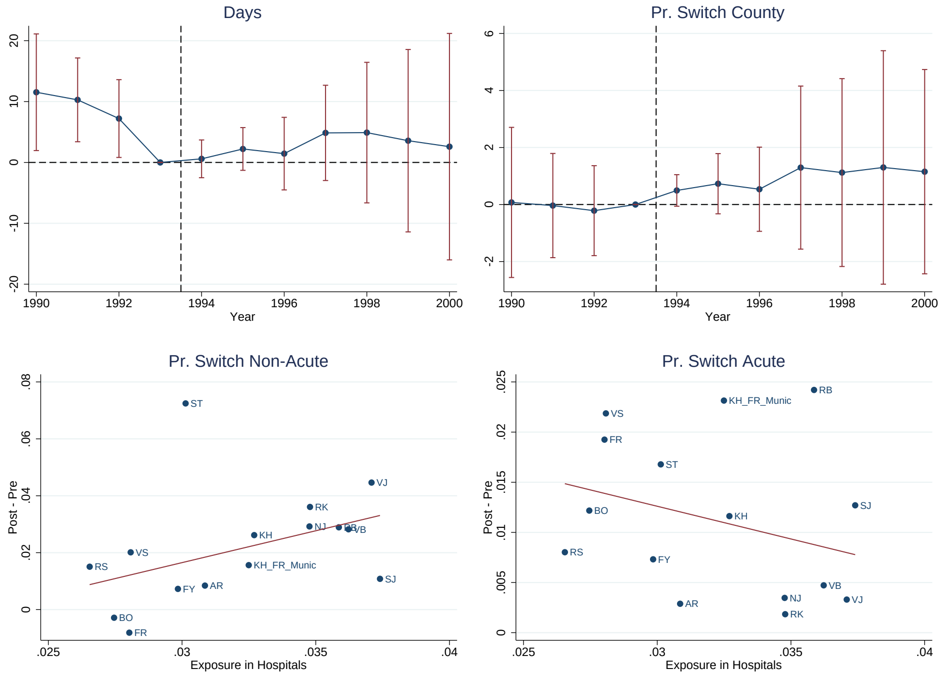
An additional margin along which health care providers can mitigate the adverse health outcomes resulting from a net reduction of nurses on staff is tho adjust the volume and the risk composition of incoming patients.

Hospitals

We first turn to changes in access to hospital care. We find no evidence for systematic changes in overall access to care measured by the number of visits per person in the population or the number of wait days prior to treatment, see the online Appendix Figure 23 for details. We also find no evidence for changes in overall number of hospital days per person in the population, which combines access to care and the length of stay, see the top left graph of Figure 12. We present the average λ coefficient in the first column of Table 6. Next, we consider patient switching between counties. To this end, we quantify the fraction of patients who choose a hospital outside their county of residence and test whether patients from highly exposed counties, based on exposure in hospitals, are more likely to switch counties. The top right graph presents the λ coefficients which provide first suggestive evidence in favor of

[37] One concern is that several counties already reach 100 % adoption rates in the pre-reform period, which would imply by construction a weakly negative change in the adoption rate. To address this concern, we drop counties with 100 % adoption rates in 1992 or 1993. The result is presented in Figure 22, which implies a qualitatively and quantitatively similar relationship.

Figure 12: Patient Management in Hospitals



this hypothesis, however the effects are relatively small in economic magnitude. The pooled λ estimate suggests an average increase in county switching of only 1.1 percentage points, see the fourth column of Table 6.

We revisit this hospital switching in the second row of Figure 12, where we split the sample population into non-acute and acute patients in the left and right graph, respectively. The graphical evidence suggests a positive relationship for non-acute patients and a negative relationship between acute patients, indicating that hospitals located on the most affected counties focus their resources on the less mobile acute care population. The average effects are not statistically significant, however, we can reject the null hypothesis of a equal slopes for non-acute patients at the 5% level which corroborates our main conclusion regarding selective patient management. Overall, this evidence provides a mechanism though which hospitals mitigate adverse patient health outcomes.

Nursing Homes

Next we turn to resident selection in nursing homes. The evidence from Figure 7 indicates a decline in the nursing home population in the later post-reform years, 1997-2000, which can partially explain the reduction in the unconditional mortality rate in these years. In this section, we provide more details on patient selection, which allows us to identify sub-populations that are less affected by the nurse reductions to the extent that they have access

Table 6: Patient Management in Hospitals

	(1) Visits	(2) Days	(3) Wait Days	(4) Switch
λ^{post}	-.23	-.62	-.16	.353
	[-1.081,.621]	[-3.012,1.772]	[-4.609,4.289]	[-.648,1.355]
Δ_1	-.065	.011	-1.142	.406
	[-.617,.488]	[-1.938,1.961]	[-3.384,1.101]	[-.183,.996]
Δ_2	-.166	.078	.133	.594
	[-.981,.649]	[-1.904,2.059]	[-3.507,3.772]	[-.254,1.441]
Δ_3	-.236	-.604	-.15	.494
	[-1.11,.639]	[-3.106,1.898]	[-4.767,4.466]	[-.752,1.74]
Pre-Reform Value	.159	.742	.37	.118
Avg. Effect	-.007	-.02	-.005	.011

The 95% confidence interval is displayed in brackets.
Standard errors are clustered at the county level. We control for log population. The delta estimates take pre-trends into account.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

to alternative informal sources of long term cares. Selection increases over time, which suggests learning about the deterioration in health care provision in nursing homes.

Our analysis distinguishes between entry decisions of elderly individuals who do not currently live in a nursing home and exit decisions of nursing home patients. Table 7 reports the results.[38] Panel A shows a decrease in entry into nursing homes across the entire population, but the decline is not precisely estimated. For the full population aged 85 and older, we estimate a reduction by 0.4 percentage points over the first three years after the reform, which corresponds to a moderate reduction in the share of nursing home residents by 4%. Using the Δ estimates following equation 2 to account for pre-existing trends, we estimate slightly larger reductions in entry rates over time. These results on entry behavior are similar across gender and marital status. Individuals who currently live on their own, either with or without family support, have access to alternative sources of care using home nursing and informal care arrangements. This patient selection might also help explain the increase in hospital mortality rates in counties with greater exposure in nursing homes as illustrated in Figure 7 if sick patients live at home longer.

The situation changes when we consider exit decisions for current nursing home residents in Panel B. Given the extent of irreversibility in deciding to live in a nursing home, both a sufficiently good health status and family support may be necessary to leave. The results illustrate higher exit rates in nursing homes with greater nurse shortages after the reform. But this increase is entirely driven by widowed and divorced women, who constitute more than 70% of women age 85 and older. Nursing home residents in this group are more than

[38] We provide the corresponding graphical evidence in Appendix Figures 24 and 25.

40% more likely to leave the nursing home over the entire period 1994-2000 after the reform. In contrast, married women whose spouse is still alive and single women do not change their propensity to move out of the nursing home. This finding is consistent with the role of family support and differential health selection into nursing homes. The average health of women who live in a nursing home despite their partner still being alive is likely worse than for other groups. Single women who were never married are less likely to have children to support them. We find that only women, but not men, increase their exit rate from nursing homes; this result holds even when comparing only the groups of widowers. This difference could be explained by age differences of children, for example, because at a given age, women have older children who are more likely to be retired and whose informal care provision is less likely to be affected by their job. Women might also be more likely to move in with their children. As a result, separated women are the marginal residents who show the strongest response to worsening conditions in nursing homes.

6.4.3 Employee Management

Finally, we investigate whether hospitals and nursing homes differ systematically in terms of the staffing fluctuations that they face due to the reform, which may also reconcile differential effects on patient health between these sectors.

Staffing management

Better capacity management may be an important reason why hospitals prevent adverse mortality effects. In order to compare fluctuations in leave taking across providers with different staffing levels, we construct the coefficient of variation for leave taking at the individual provider level based on the exact timing of leave taking, reported by social benefit data for 1995-2000. Since both hospitals and nursing homes face strong seasonality in leave taking, we analyze capacity management of health care providers within months.[39] In particular, we take the standard deviation of leave takers per day within each month, relative to the average monthly number of leavers. Figure 13 shows the distribution of monthly coefficients of variation for hospitals and nursing homes.[40] Months without any inflow or outflow are common in nursing homes, but, at the same time, these providers face very high fluctuation in other months. Overall, this evidence suggests that hospitals are more likely to avoid peak shortages which might have large adverse effects.

[39] Appendix Figure 13 illustrates these seasonal differences in leave taking. In general, the number of nurses on leave peaks in June and July and decreases during the winter months.

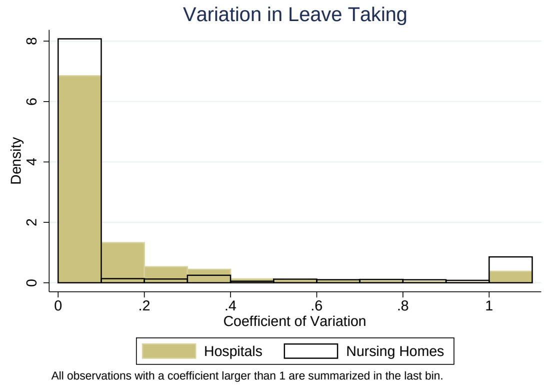
[40] We focus on all individual providers with at least two skilled nurses and set the coefficient of variation to zero for months without leavers. We group coefficients larger than 1 in the last bin.

Table 7: Patient Selection: Entry and Exit Decisions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Entry	Total	All Men	All Women	Women by Marital Status		
				Married	Separated	Single
λ^{94-96}	-.24	-.032	-.346	.065	-.289	-1.128
	[-1.446,.966]	[-1.199,1.136]	[-1.586,.894]	[-1.94,2.07]	[-1.554,.975]	[-2.653,.396]
λ^{97-00}	-.024	-.656	.222	-1.095	.547	-1.079
	[-1.111,1.062]	[-1.706,.394]	[-.952,1.396]	[-2.974,.784]	[-.553,1.647]	[-3.326,1.167]
Δ_1	-1.673	-1.509	-1.845	1.987	-2.355	-1.75
	[-4.435,1.089]	[-5.341,2.322]	[-4.817,1.127]	[-1.798,5.772]	[-6.048,1.338]	[-6.884,3.384]
Δ_2	-1.859	-1.017	-2.295	-2.613*	-1.616	-7.087***
	[-5.876,2.158]	[-5.18,3.146]	[-6.412,1.821]	[-5.599,.373]	[-6.4,3.168]	[-11.914,-2.26]
Δ_5	-2.599	-3.358	-2.334	-3.745**	-1.354	-8.151***
	[-6.356,1.158]	[-7.581,.866]	[-6.093,1.425]	[-7.427,-.063]	[-5.714,3.006]	[-12.639,-3.662]
Pre-Reform Value	.103	.107	.095	.093	.107	.117
Avg. Effect, 94-96	-.004	-.006	-.001	.001	-.005	-.018
Avg. Effect, 97-00	0	.004	-.011	-.018	.009	-.018
Panel B: Exit	Total	All Men	All Women	Women by Marital Status		
				Married	Separated	Single
λ^{94-96}	1.28	-.21	1.597	-3.735	1.995*	.622
	[-1.348,3.909]	[-4.327,3.908]	[-.736,3.929]	[-9.366,1.897]	[-.286,4.276]	[-3.673,4.917]
λ^{97-00}	1.948	.593	2.235*	2.226	2.334*	1.696
	[-.486,4.382]	[-2.553,3.74]	[-.101,4.57]	[-1.287,5.739]	[-.108,4.775]	[-2.195,5.588]
Δ_1	2.543	-.767	3.56	-9.827	4.969***	-2.201
	[-2.369,7.455]	[-10.278,8.744]	[-.78,7.9]	[-22.694,3.04]	[1.126,8.813]	[-13.669,9.267]
Δ_2	-.42	-6.743**	1.394	-9.993	3.228*	-6.502
	[-5.117,4.278]	[-13.438,-.048]	[-2.847,5.635]	[-28.135,8.149]	[-.533,6.99]	[-18.496,5.492]
Δ_5	2.707	-2.801	4.412**	-4.803	5.868***	-2.034
	[-1.31,6.724]	[-8.663,3.061]	[.529,8.295]	[-19.383,9.777]	[2.408,9.328]	[-13.689,9.621]
Pre-Reform Value	.079	.076	.093	.08	.076	.077
Avg. Effect, 94-96	.021	.026	-.003	-.061	.032	.01
Avg. Effect, 97-00	.032	.036	.01	.036	.038	.028

The 95% confidence interval is displayed in brackets. Standard errors are clustered at the county level.
Separated includes divorced and widowed. Married is based on the partner being still alive.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

Figure 13: Parental Leave and Staffing Management



Next, we further use the data on benefit spells to analyze whether health care providers differ in their influence on take-up and leave duration. To this end, we display the OLS regression coefficient of exposure on a leave taking indicator variable that turns on whether the eligible nurse is on leave in the given year, and a leave duration indicator variable among leave takers that turns on whether the leave exceeds 26 weeks, in odd and even columns of Table 8, respectively. The first two columns present the coefficients for the full sample of hospitals and nursing homes before we split the sample into hospitals, columns (3) and (4), and nursing homes, columns (5) and (6). The table shows two main results. First, both hospitals and nursing homes cannot affect the extensive margin of leave taking among eligible parents. Columns (1), (3) and (5) show that higher exposure does not affect the probability of leave taking among eligible parents. The parental leave reform entitled all parents with children up to 8 years of age to take 26 weeks of leave without employer approval. In line with the policy design, leave taking depends on worker preferences and cannot be influenced by employers. Second, columns (2), (4) and (6) analyze the intensive margin of leave taking among leavers. Even though parents are entitled to leave, employers can influence the duration of leave because extended leave of up to 52 weeks needed employer approval. As a result, the probability of extended leave reflects employer preferences. We find that hospitals that are more exposed to the reform are more likely to prevent *extended* leave taking of their nurses, as indicated by the statistically significant negative coefficient in column (4). Yet, while hospitals with average exposure reduce the probability of extended leave among leavers by 18.3 percentage points, there is no significant reduction in nursing homes with higher exposure. One explanation for the differences in behavior across providers could be that hospitals have greater bargaining power in their efforts to retain employees, if necessary. As a result, hospitals may be better able to retain qualified workers and to stabilize the workforce overall.

Table 8: Employer Approval for Extended Leave

	(1) leave	(2) >26 wks | l=1	(3) leave	(4) >26 wks | l=1	(5) leave	(6) >26 wks | l=1
exposure	0.140	-1.696***	-0.522	-5.547***	-0.0485	-0.531
	(1.323)	(-3.959)	(-1.145)	(-4.618)	(-0.348)	(-0.655)
Observations	91,218	12,854	71,100	11,003	13,024	1,216
R-squared	0.232	0.045	0.242	0.044	0.181	0.090
Share of Leavers	0.137	0.289	0.155	0.275	0.0923	0.366
Av. Effect	0.00400	-0.0540	-0.0170	-0.183	-0.00100	-0.0110

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

These adjustment mechanisms in combination with the differences in mortality effects across hospitals and nursing homes suggest an important role for nonlinearities in the health production function. Specifically, we hypothesize that large exposures lead to disproportionately drastic negative consequences, if left unaddressed. We revisit the employer efforts to mitigate the adverse staffing implications of large policy exposures in Figure 14, where we present nonparametric Epanechnikov kernel estimates and 95% confidence intervals for the conditional probability of extended leave among leavers. We find that the share of extended leave takers is much lower at providers with high exposure. Yet hospitals proportionately reduce the share of extended leave according to the overall fraction of leavers, whereas the share of extended leave in nursing homes is stable across a wide range of exposure and only declines for facilities with very high exposure levels.[41] Figure 14 also emphasizes the level differences in extended leave taking across hospitals and nursing homes, with hospitals avoiding extended leave much more frequently. In sum, providers with the largest exposure show the strongest endogenous response to prevent large nurse shortages and adverse health outcomes for patients. Hospitals are more effective in avoiding staffing fluctuations and in preventing extended leave. As a result, the relationship between exposure and patient health outcomes is weaker and noisier for these providers.

Human capital and workforce composition

Secondly, we analyze the relative change in average experience of nurses in hospitals and nursing homes. Nurses acquire industry-specific human capital over time, for example, by treating similar types of patients repeatedly. The large mortality effects in nursing homes

[41] In general, estimates of health effects at the provider level will be biased if endogenous adjustments are strongest at providers with greatest exposure because this response leads to a nonlinear relationship between exposure and health outcomes. Our aggregation at the county level mitigates this potential bias at the provider level.

Figure 14: Nonlinearities in Employer Responses

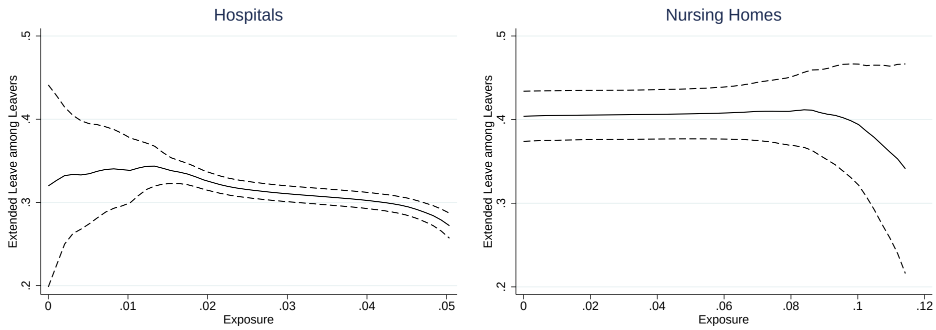
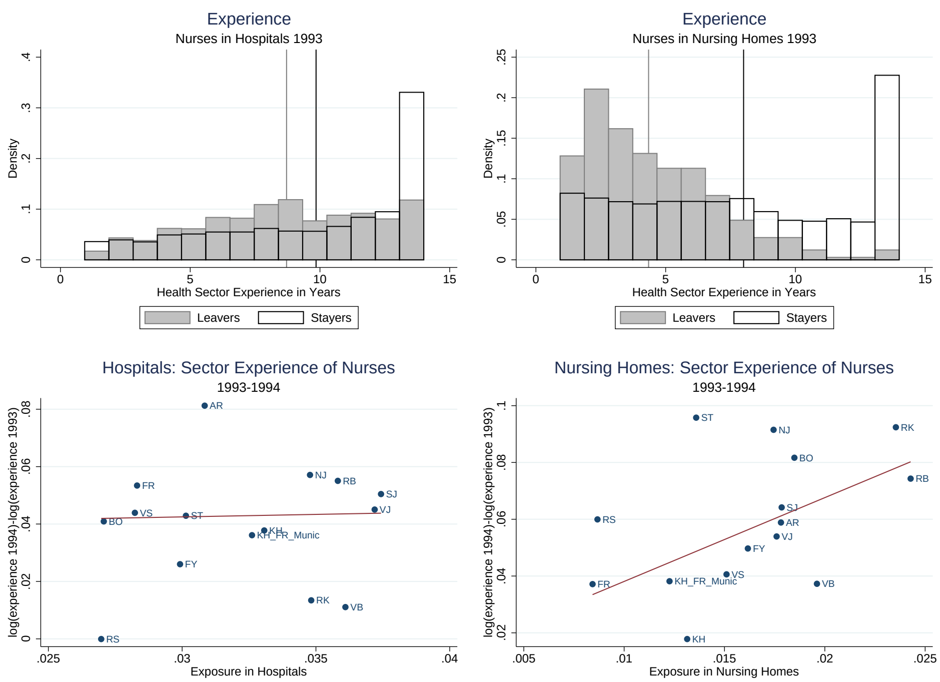


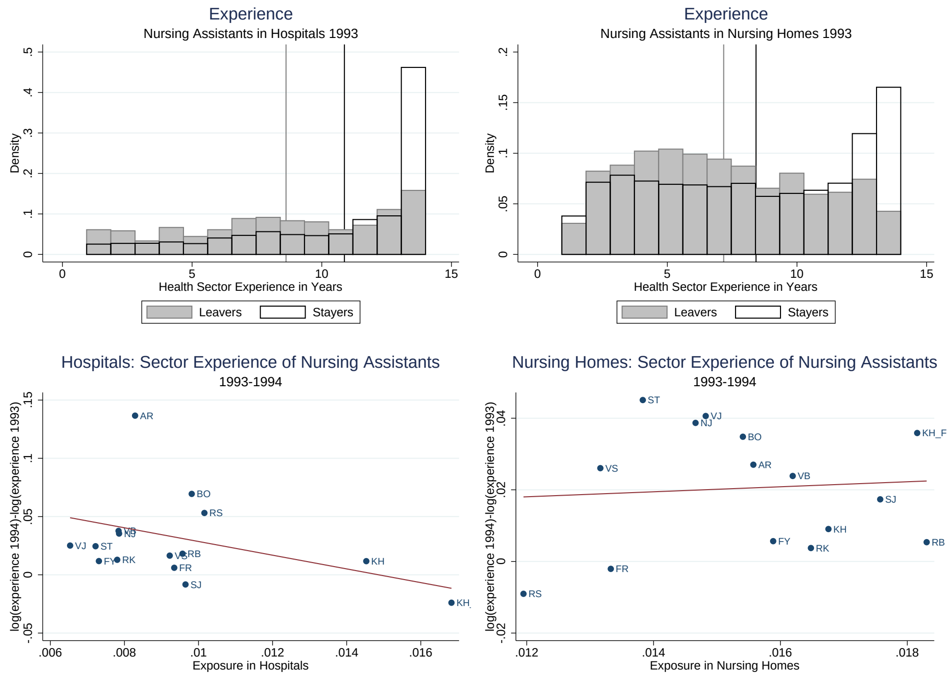
Figure 15: Industry Experience and Changes in Human Capital among Nurses 1993-1994



could be explained by a stronger reduction in this human capital stock compared to hospitals. Our main analysis focuses on the number of nurses and abstracts from this channel. In order to assess the importance of this mechanism, this section takes the relative change in nurse experience into account.

Specifically, we measure experience of each nurse by health care sector as the number of years the person has been employed in hospitals or nursing homes respectively. In practice, the distribution of total experience is truncated because we only observe individuals from 1980 onwards. The first row of Figure 15 illustrates differences in industry experience between parental leave takers, who take a leave of absence in 1994 and were eligible for the child leave program at that time, and stayers who continuously work in the sector in 1993 and 1994.

Figure 16: Industry Experience and Changes in Human Capital among Nursing Assistants 1993-1994



The vertical lines in the figure represent average experience of stayers and leavers in the two sectors. We find that leavers in nursing homes are less experienced than those in hospitals, both in levels and relative to stayers.[42] As a result, a composition effect will lead to a stronger increase of average experience in nursing homes than in hospitals after the reform. This channel is reflected in the second row of Figure 16, which shows a stronger increase in average experience of nurses in counties with higher exposure to the reform and this patterns is particularly pronounced for nursing homes. Based on this evidence, we conclude that the increase in mortality rates in nursing homes is not mainly caused by a loss in the average human capital stock of nurses but rather the result of the strong reduction in the number of nurses.

Another alternative explanation could be compositional changes in the stock of nursing assistants. The previous evidence on nursing assistants showed that takeup rates among this group are high but providers are able to replace these workers through new hires. As a result, average experience among assistants may also decline more in counties with higher exposure that need to recruit more job switchers and newly educated assistants. In general,

[42]Overall, the age distribution of leavers with children age 8 or younger is very similar for hospitals and nursing homes, see Figure 20. Nursing home staff is older, on average, but many have less nursing home industry experience because they have worked in other sectors for part of their career. As a result, average experience of stayers in nursing homes is lower than in hospitals.

this pattern could contribute to adverse patient health effects in counties with greater exposure. Yet, as the second row of Figure 16 illustrates, average experience is only negatively correlated with exposure in hospitals. Nursing homes in counties with greater exposure do not systematically lose a larger fraction of their human capital stock among nursing assistants. The reason for this difference is the much lower experience distribution among nursing assistants in nursing homes. The first row of Figure 16 shows that the majority of leave takers have fewer than five years of experience. Hence the experience composition is hardly affected by replacing these leavers with inexperienced job switchers or entrants. In sum, this evidence suggests that the large health effects in nursing homes are unlikely to be driven by systematic loss of experience among nursing assistants.

7 Conclusion

Nurses make up the largest health profession and play a critical role in the delivery of health care services. In this paper, we take advantage of a natural experiment in Denmark to quantify the effect of nurses on health care delivery and patient health across health sectors. Specifically, we investigate the consequences of a parental leave program which led and unintended, sudden, and persistent 12% reduction in nurse employment. We find evidence for modest detrimental effects on hospital care delivery as indicated by an increase in 30-day readmission rates and a distortion of technology utilization. Our findings for nursing homes are more drastic indicating a 13% increase in nursing home mortality among the elderly aged 85 and older.

Our results suggest a larger return of nurses on health care delivery in nursing homes, which we can reconcile through a theoretical hierarchy model that illustrates the greater responsibility of a nurse in the nursing home. The theoretical model also formalizes the resident monitoring role of the nurse, which is an integral input to the hospitalization decision of the sickest nursing home residents. The model predicts that the reduced nurse-resident time deteriorates the monitoring quality, which results in a reduced hospitalization rate of the most needy residents. This prediction holds true in the data. In fact, our findings suggest that a substantial fraction of nursing home deaths might have been postponed, had the needy residents had access to the hospital.

Overall, our estimates provide evidence for a mis-allocation of nurses between sectors. This is a topic of growing policy relevance as the demand for health care services increases and a large fraction of nurses reach the retirement age in developed countries. While policy makers have primarily considered instruments to raise the overall supply of nurses including education and immigration programs, less is known about how nurses are allocated between sectors. Understanding how policy instruments, including minimum nurse-to-patient ratios or wage subsidies, can increase nurse employment in nursing homes in particular is therefore of policy interest in the context of an aging population and disproportionately growing demand for long term care services, and subject of future research.

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Online Appendix

A Institutions and Policy Reform

Figure 17: Counties of Denmark 1970-2006

	Description	Our Code
1+2	Copenhagen and Frederiksberg Municipalities	CPH-FR Munic
3	Copenhagen County	KH
4	Frederiksborg County	FR
5	Roskilde County	RS
6	West Zealand County	VS
7	Storstrom County	ST
8	Funen County	FY
9	South Jutland County	SJ
10	Ribe County	RB
11	Vejle County	VJ
12	Ringkjobing County	RK
13	Viborg County	VB
14	North Jutland County	NJ
15	Aarhus County	AR
16	Bornholm	BO

Table 9: Leave Program Take-Up

Number of full-time equivalent leavers among nurses			
	Parental leave	Education leave	Sabbatical leave
1995	2108	516	129
1996	1606	575	<10
1997	1296	517	<10
1998	1114	317	<5
1999	1133	282	<5
2000	1130	205	<5

Figure 18: Duration of Leave Benefits: Education and Parental Leave

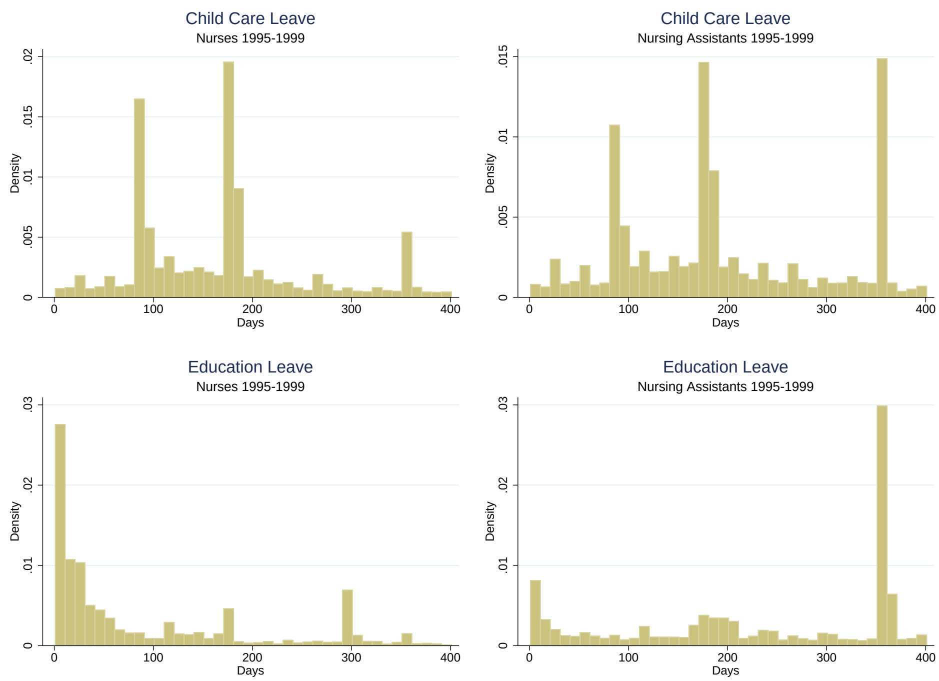


Figure 19: Timing of Parental Leave Taking

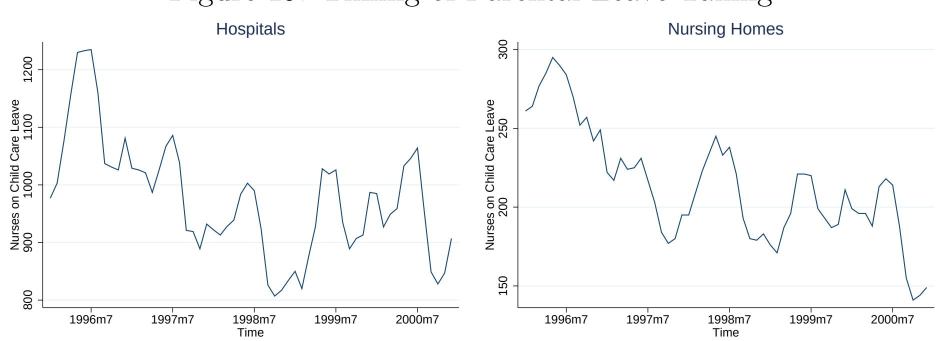
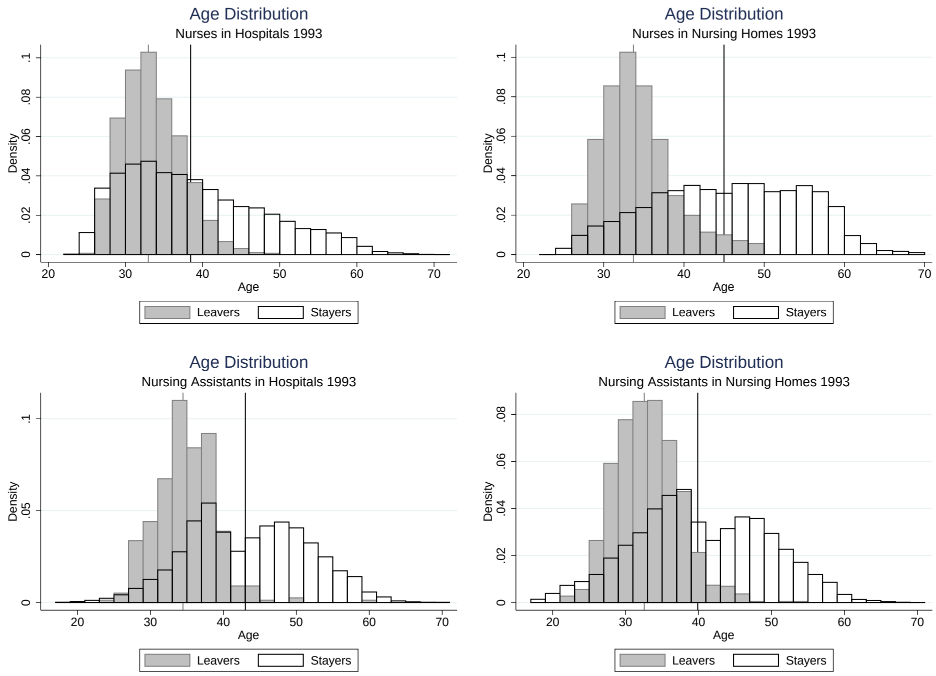


Figure 20: Age Distribution of Leavers and Stayers 1993-1994



B Estimation Results and Robustness

B.1 Regression Results for Program Takeup

Table 10: Program Take-Up

	(1)	(2)	(3)	(4)	(5)	(6)
	Nurses	Assistants	Doctors	Nurses	Assistants	Doctors
	1993 vs 1994			1993 vs 1995		
Age0 x Post-Reform	0.2000***	0.1607***	0.0173**	0.1877***	0.1068***	0.0161**
	(0.006)	(0.010)	(0.007)	(0.006)	(0.009)	(0.007)
Age1 x Post-Reform	0.1706***	0.2445***	-0.0024	0.1142***	0.1885***	0.0126*
	(0.006)	(0.010)	(0.007)	(0.006)	(0.010)	(0.007)
Age2 x Post-Reform	0.0982***	0.1029***	-0.0004	0.0253***	0.0090	-0.0072
	(0.007)	(0.010)	(0.007)	(0.006)	(0.011)	(0.007)
Age3 x Post-Reform	0.0734***	0.0686***	-0.0112	0.0352***	0.0102	0.0003
	(0.007)	(0.010)	(0.008)	(0.007)	(0.010)	(0.008)
Age4 x Post-Reform	0.0636***	0.0611***	0.0047	0.0251***	0.0281***	-0.0060
	(0.008)	(0.010)	(0.009)	(0.007)	(0.010)	(0.008)
Age5 x Post-Reform	0.0452***	0.0336***	-0.0093	0.0355***	0.0206**	-0.0060
	(0.008)	(0.010)	(0.009)	(0.008)	(0.010)	(0.009)
Age6 x Post-Reform	0.0401***	0.0589***	-0.0028	0.0335***	0.0219**	-0.0061
	(0.009)	(0.011)	(0.009)	(0.008)	(0.010)	(0.009)
Age7 x Post-Reform	0.0508***	0.0469***	0.0006	0.0264***	0.0251**	0.0007
	(0.009)	(0.011)	(0.009)	(0.008)	(0.010)	(0.009)
Age8 x Post-Reform	0.0425***	0.0499***	-0.0007	0.0025	0.0179*	-0.0023
	(0.009)	(0.011)	(0.009)	(0.008)	(0.011)	(0.009)
Post-Reform	0.0132***	0.0274***	0.0021	0.0167***	0.0371***	-0.0002
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	58,532	52,517	17,358	56,363	50,445	17,420
R-squared	0.088	0.064	0.008	0.073	0.043	0.008

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

B.2 Details on Estimation Results

Table 11: Regression Results for Employment

	(1) Total	(2) Hosp and NH	(3) Hosp	(4) NH
λ_{1990}	-3.322**	-0.820	-2.833	-5.699
	[-5.811,-0.834]	[-6.417,4.776]	[-10.10,4.438]	[-16.19,4.787]
λ_{1991}	-1.822**	-2.098*	-2.113	-5.395
	[-3.535,-0.110]	[-4.496,0.300]	[-6.644,2.419]	[-12.67,1.875]
λ_{1992}	-0.393	-1.152*	-0.869	-3.023
	[-1.635,0.848]	[-2.404,0.100]	[-3.035,1.296]	[-8.467,2.421]
λ_{1994}	-2.525***	-3.808***	-3.131	-4.881**
	[-4.263,-0.786]	[-5.816,-1.801]	[-7.220,0.959]	[-9.058,-0.704]
λ_{1995}	-4.963*	-5.599**	-5.538*	-4.929**
	[-10.69,0.768]	[-10.28,-0.920]	[-11.89,0.812]	[-9.835,-0.0240]
λ_{1996}	-6.094**	-5.658**	-4.935	-4.145
	[-12.16,-0.0279]	[-9.764,-1.553]	[-11.48,1.614]	[-10.16,1.873]
λ_{1997}	-5.429	-5.745**	-3.993	-6.117
	[-14.17,3.308]	[-11.48,-0.00469]	[-12.37,4.388]	[-14.02,1.784]
λ_{1998}	-5.095	-3.450	-2.064	-4.647
	[-13.90,3.712]	[-9.854,2.953]	[-11.90,7.775]	[-13.04,3.744]
λ_{1999}	-4.972	-4.138	-2.632	-4.936
	[-14.34,4.395]	[-11.24,2.961]	[-13.11,7.849]	[-16.01,6.141]
λ_{2000}	-8.304*	-5.868	-5.220	-3.692
	[-18.17,1.558]	[-13.36,1.624]	[-16.55,6.108]	[-16.70,9.313]
Controls				
N	165	165	165	165

95% confidence intervals in brackets
Note: Standard errors are clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Robustness to Differences in Mortality Risks

We address potential differences in mortality risks between counties and over time in additional robustness checks. To this end, we combine age and gender information from IDAP with information on inpatient acute care hospitalizations from the Danish National Patient Register. Specifically, we calculate the number and the total length of this and the previous year's hospital visits for each elderly person. To leverage the rich demographic and health utilization information in our analysis we proceed in three steps. First, we regress a mortality indicator variable on age-gender fixed effects, county-year fixed effects, as well as current and last year's length and number of hospital visits at the person-year level. Second, we keep the predicted county-year fixed effects which capture differences in mortalities between counties and over time conditional on differences in the mortality risks as measured by the age-gender composition and the frequency of hospitalizations. Finally, we use these residualized mortality rates in our following county-year level regression analysis.

Table 12: Mortality by Nursing Home Exposure: Age 85 and older

	(1) Tot	(2) Tot	(3) Hosp	(4) Hosp	(5) NH	(6) NH
λ_{1991}	-0.084	-0.38	-0.10	-0.30	-0.00044	-0.080
	[-0.86,0.69]	[-1.24,0.49]	[-0.70,0.49]	[-0.80,0.20]	[-0.59,0.59]	[-0.71,0.56]
λ_{1992}	0.47	0.24	0.12	-0.038	0.10	0.049
	[-0.67,1.61]	[-0.82,1.31]	[-0.59,0.83]	[-0.63,0.55]	[-0.88,1.09]	[-0.91,1.01]
λ_{1994}	0.55	0.56	-0.22	-0.21	0.66***	0.64***
	[-0.47,1.57]	[-0.31,1.44]	[-0.77,0.34]	[-0.66,0.24]	[0.24,1.08]	[0.25,1.04]
λ_{1995}	0.45	0.52	0.0038	0.040	0.48*	0.49*
	[-0.37,1.26]	[-0.22,1.26]	[-0.27,0.28]	[-0.17,0.25]	[-0.067,1.03]	[-0.072,1.05]
λ_{1996}	0.90**	0.90**	-0.017	-0.069	0.90**	0.90**
	[0.051,1.76]	[0.13,1.68]	[-0.39,0.36]	[-0.36,0.22]	[0.24,1.56]	[0.23,1.58]
λ_{1997}	0.062	0.095	0.14	0.11	0.23	0.24
	[-0.65,0.78]	[-0.60,0.79]	[-0.42,0.70]	[-0.45,0.66]	[-0.46,0.92]	[-0.50,0.97]
λ_{1998}	0.98**	0.85**	0.52***	0.36**	0.54	0.51
	[0.16,1.80]	[0.032,1.66]	[0.16,0.89]	[0.053,0.68]	[-0.15,1.23]	[-0.18,1.20]
λ_{1999}	0.20	0.077	0.45	0.27	-0.047	-0.048
	[-0.57,0.97]	[-0.57,0.72]	[-0.25,1.14]	[-0.082,0.62]	[-0.65,0.56]	[-0.81,0.71]
λ_{2000}	0.51	0.18	0.44	0.11	0.20	0.17
	[-0.62,1.63]	[-0.72,1.07]	[-0.12,1.00]	[-0.10,0.31]	[-0.50,0.91]	[-0.59,0.93]
Controls	✗	✓	✗	✓	✗	✓
N	150	150	150	150	150	150

95% confidence intervals in brackets
Note: Standard errors are clustered at the county level. In columns 2, 4, and 6 we added further controls including previous hospitalizations and age-gender fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Robustness to Patient Characteristics

Table 13: Hospital Outcomes: Robustness

	(1) Mortality Acute	(2) Mortality Newborns	(3) Readmission	(4) Readmission Newborn
λ	.395	1.022	1.137***	.534**
	[-.888,1.677]	[-.807,2.851]	[.398,1.876]	[.048,1.02]
Δ_1	-.908	.22	1.263***	.388
	[-3.049,1.233]	[-3.089,3.528]	[.501,2.025]	[-.257,1.033]
Δ_2	.144	-.149	.849***	.41
	[-1.127,1.415]	[-2.705,2.407]	[.176,1.523]	[-.11,.93]
Δ_3	.29	.637	1.055***	.357
	[-1.034,1.614]	[-1.03,2.304]	[.416,1.695]	[-.183,.896]
Pre-Reform Value	.254	.06	.187	.036
Avg. Effect	.013	.033	.037	.017

The 95% confidence interval is displayed in brackets.
Standard errors are clustered at the county level. For babies, we flexibly control for birth weight.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

Table 14: Nursing Home Outcomes: Robustness

	(1) NH (uncond.)	(2) Total	(3) Hosp	(4) NH Pop Share	(5) NH (cond.)
λ	.673***	.702***	0.036	-1.521***	3.286***
	[.335,1.01]	[.417,.987]	[-.189,.262]	[-2.745,-.298]	[1.753,4.82]
Δ_1	.644***	0.564	-0.211	-.956*	2.167
	[.285,1.003]	[-.232,1.36]	[-.624,.203]	[-2.022,.11]	[-.488,4.822]
Δ_2	.542***	.423***	-0.066	-0.753	2.671***
	[.165,.918]	[.159,.688]	[-.337,.205]	[-2.524,1.018]	[1.046,4.297]
Δ_3	.688***	.708***	0.032	-1.283	3.284***
	[.317,1.059]	[.421,.995]	[-.207,.271]	[-3.51,.943]	[1.71,4.857]
Pre-Reform Value	0.079	0.165	0.058	0.256	0.328
Avg. Effect	0.011	0.011	0.001	-0.025	0.053

Note: The dependent variable in columns (1)-(3) is mortality relative to the county population, column (4) the population share of NH residents, column (5) mortality relative to NH residents. The 95% confidence interval is displayed in brackets. Standard errors are clustered at the county level. We control for previous hospitalizations and age-gender fixed effects.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

C Model Proofs

C.1 Proof of Lemma 1

In the nursing home, health status of patients is unknown when nurses commit to the time spent per patient. As a result, nurses distribute their time budget equally.[43]

For hospital workers, assume a worker faces some distribution of cases with probability p for high risk patients r and $1-p$ for normal patients $n < r$. The worker maximizes patient health subject to a time constraint,

$$\max_{t_n,t_r} (1-p) f(n,t_n) + pf(r,t_r)$$
$$\text{s.t.} (1-p) t_n + pt_r = T.$$

The first order condition implies

$$f_t(n,t_n) = f_t(r,t_r)$$

but by definition $n < r$ and using $f_{tt} < 0$ and $f_{ts} > 0$ in hospitals this yields

$$t_n < t_r.$$

C.2 Proof of Proposition 1

Suppose for simplicity that nurse and doctor treatment time are additively separable. Then the only change for hospital patients is due to changes in nursing time.

To see optimal adjustment of nurses, substitute the time budget constraint into the FOC,

$$f_t(r,t_r) - f_t\left(n, \frac{T}{1-p} - \frac{p}{1-p} t_r\right) = 0$$
$$f_t(n,t_n) - f_t\left(r, \frac{T}{p} - \frac{1-p}{p} t_n\right) = 0$$

[43] If we allow for treatment based on diagnosis information, the assumption of $f_{ts} = 0$ implies equal treatment time across patients. If nurses are more effective in treating higher risk patients, then patients with a higher signal will receive more treatment subsequently.

and use the implicit function theorem to yield

$$\frac{dt_r}{dT} = \frac{\frac{1}{1-p} f_{tt}(n,t_n)}{f_{tt}(r,t_r) + \frac{p}{1-p} f_{tt}(n,t_n)} = \frac{f_{tt}(n,t_n)}{p f_{tt}(n,t_n) + (1-p) f_{tt}(r,t_r)} > 0$$

$$\frac{dt_n}{dT} = \frac{\frac{1}{p} f_{tt}(r,t_r)}{f_{tt}(n,t_n) + \frac{1-p}{p} f_{tt}(r,t_r)} = \frac{f_{tt}(r,t_r)}{p f_{tt}(n,t_n) + (1-p) f_{tt}(r,t_r)} > 0$$

which implies that

$$\frac{dt_n}{dT} > \frac{dt_r}{dT} \Leftrightarrow f_{tt}(r,t_r) < f_{tt}(n,t_n).$$

Since the second derivative is negative, this result implies that the value at the optimal treatment time for normal patients is less negative. Assumption (3) describes the curvature of the health function by patient type, with more curvature for sicker patients conditional on time used. As a result,$f_{tt}(r,t_r) < f_{tt}(n,t_r)$. But since $t_n < t_r$, the third derivative with respect to time will also matter. For the result to hold, f_{ttt} has to be sufficiently small (cannot be too positive). Note that $f_{ttt} \leq 0$ is a sufficient condition because then the second derivative is more negative for larger values of time input, $f_{tt}(n,t_r) < f_{tt}(n,t_n)$.

Finally, changes in health outcomes are a linear function of changes in time input,

$$\frac{dy_n}{dT} = f_t(n,t_n)\frac{dt_n}{dT}$$
$$\frac{dy_r}{dT} = f_t(r,t_r)\frac{dt_r}{dT}$$

and using the FOC,

$$\frac{dt_n}{dT} > \frac{dt_r}{dT} \Leftrightarrow \frac{dy_n}{dT} > \frac{dy_r}{dT}.$$

Note that if nursing and doctor time are complements, the reallocation of time towards high risk patients may be more pronouced because doctors have a comparative advantage in treating high risk patients and this treatment requires nurse input as well.

C.3 Proof of Proposition 2

In nursing homes, a reduction in nursing staff leads to an adjustment in diagnosis time. As the total time budget of nurse staff decreases, time spent with each resident decreases proportionally,

$$\frac{dt}{dN} = \frac{T}{M}.$$

The reduction in time per patient has several implications. First, the overall share p of high risk patients among nursing home residents will increase because $\frac{\partial}{\partial t} p_{n,r} < 0$. Intuitively, regular patients receive less attention and become more likely to develop complications. At the same time, high risk patients are less likely to recover with lower treatment intensity, $\frac{\partial}{\partial t}p_{r,n} < 0$.

Second, the reduction in the recovery rate of high risk patients is exacerbated by a deterioration in diagnosis. Less time per patient implies that nurses will receive noisier health signals,$\sigma'(t) < 0$, about all patients. As a consequence, a larger share of high risk patients will not receive hospital treatment.

Note that in general, the probability of patients with risk type s staying in the nursing home is given by

$$Pr\left(v < v^* \,|\, s\right) = G_s\left(v^*\right) = \Gamma\left(\frac{v^* - s}{\sigma}\right)$$

where the signal $v \sim G_s\left(s, \sigma\left(t\right)\right)$ and Γ is the normalized signal distribution with mean zero and variance equal to one. Allowing for a change in the hospitalization cutoff, the change in this probability for patient type $s \in \{n, r\}$ as the diagnosis time changes is given by

$$\frac{d}{dt}Pr\left(v < v^* \,|\, s\right) = \gamma\left(\frac{v^* - s}{\sigma}\right)\sigma'\left(t\right) \cdot \frac{\frac{dv^*}{d\sigma}\sigma - \left[v^* - s\right]}{\sigma^2}.$$

We illustrate the effect of a noisy signal on the separation of patient types during diagnosis: More sick types are sent to the hospital while normal patients are more likely to stay in the nursing home: $\frac{d}{dt}Pr\left(v < v^* \,|\, r\right) < 0$ and $\frac{d}{dt}Pr\left(v < v^* \,|\, n\right) > 0$. This is equivalent to showing that

$$\frac{v^* - n}{\sigma} > \frac{dv^*}{d\sigma} > \frac{v^* - r}{\sigma}.$$

Rewriting equation (5) with the standardized density functions yields

$$\frac{\gamma\left(\frac{v^* - r}{\sigma}\right)}{\gamma\left(\frac{v^* - n}{\sigma}\right)} - \frac{1 - p}{p} \cdot \frac{c}{\Delta y - c} = 0.$$

Using the implicit function theorem for this condition yields

$$\begin{aligned}
\frac{dv^*}{d\sigma} &= \frac{\left(\frac{v^* - r}{\sigma^2}\right)\gamma'\left(\frac{v^* - r}{\sigma}\right)\gamma\left(\frac{v^* - n}{\sigma}\right) - \left(\frac{v^* - n}{\sigma^2}\right)\gamma'\left(\frac{v^* - n}{\sigma}\right)\gamma\left(\frac{v^* - r}{\sigma}\right)}{\frac{1}{\sigma}\gamma'\left(\frac{v^* - r}{\sigma}\right)\gamma\left(\frac{v^* - n}{\sigma}\right) - \frac{1}{\sigma}\gamma'\left(\frac{v^* - n}{\sigma}\right)\gamma\left(\frac{v^* - r}{\sigma}\right)} \\
&= \frac{v^* - r}{\sigma} + \frac{\left(\frac{n - r}{\sigma}\right)\gamma'\left(\frac{v^* - n}{\sigma}\right)\gamma\left(\frac{v^* - r}{\sigma}\right)}{\gamma'\left(\frac{v^* - r}{\sigma}\right)\gamma\left(\frac{v^* - n}{\sigma}\right) - \gamma'\left(\frac{v^* - n}{\sigma}\right)\gamma\left(\frac{v^* - r}{\sigma}\right)}
\end{aligned}$$

where the second line adds and subtracts $\left(\frac{v^* - r}{\sigma^2}\right)\gamma'\left(\frac{v^* - n}{\sigma}\right)\gamma\left(\frac{v^* - r}{\sigma}\right)$. As a result, $\frac{dv^*}{d\sigma} > \frac{v^* - r}{\sigma}$ if the second term in the last line is positive. If we assume that G is normally distributed, then the condition is always satisfied with $v^* > n$,

$$\begin{aligned}\frac{dv^*}{d\sigma} &= \frac{v^*-r}{\sigma} + \frac{-\left(\frac{n-r}{\sigma}\right)\frac{v^*-n}{\sigma}exp\left(\frac{v^*-n}{\sigma}\right)^2 exp\left(\frac{v^*-r}{\sigma}\right)^2}{-\frac{v^*-r}{\sigma}exp\left(\frac{v^*-r}{\sigma}\right)^2 exp\left(\frac{v^*-n}{\sigma}\right)^2 + \frac{v^*-n}{\sigma}exp\left(\frac{v^*-n}{\sigma}\right) exp\left(\frac{v^*-r}{\sigma}\right)} \\ &= \frac{v^*-r}{\sigma} + \frac{v^*-n}{\sigma} \Leftrightarrow \frac{dv^*}{d\sigma} > \frac{v^*-r}{\sigma}.\end{aligned}$$

There exist parameter combinations of costs and benefits of hospitalization such that this condition is satisfied. These assumptions are reasonable because in the data the hospitalization rate is about 21%.

The analogous derivation based on the probability of normal patients staying in the nursing home is given by

$$\frac{dv^*}{d\sigma} = \frac{v^*-n}{\sigma} + \frac{\left(\frac{r-n}{\sigma}\right)\gamma'\left(\frac{v^*-r}{\sigma}\right)\gamma\left(\frac{v^*-n}{\sigma}\right)}{\gamma'\left(\frac{v^*-n}{\sigma}\right)\gamma\left(\frac{v^*-r}{\sigma}\right) - \gamma'\left(\frac{v^*-r}{\sigma}\right)\gamma\left(\frac{v^*-n}{\sigma}\right)}.$$

Suppose $n < v^* < r$. Then the numerator is strictly positive, but the denominator is strictly negative and overall, we find that

$$\frac{dv^*}{d\sigma} < \frac{v^*-n}{\sigma} \Leftrightarrow \frac{d}{dt}Pr\left(v < v^* \,|\, n\right) > 0.$$

In contrast, suppose $n < r < v^*$. Then the numerator is strictly negative, while the sign of the denominator is strictly positive if γ is a concave function with $\gamma'' < 0$ in the relevant range. Yet this is a contradiction. In sum, we characterize conditions under which a noisier signal leads to a higher share of healthy types and a lower share of high risk types being transferred to the hospital.

In the next step, we add information about the patient mix among nursing home residents to analyze total hospitalizations,

$$Pr\left(v < v^*\right) = p\Gamma\left(\frac{v^*-r}{\sigma}\right) + (1-p)\,\Gamma\left(\frac{v^*-n}{\sigma}\right) = \Gamma\left(\frac{v^*-(pr+(1-p)\,n)}{\sigma}\right).$$

$$\frac{d}{dt}Pr\left(v < v^*\right) = \underbrace{\gamma\left(\frac{v^*-m}{\sigma}\right)\frac{\frac{dv^*}{d\sigma}\sigma - [v^*-m]}{\sigma^2}\cdot\frac{d\sigma}{dt}}_{\equiv A\text{: noisy diagnosis}} + \underbrace{\gamma\left(\frac{v^*-m}{\sigma}\right)\frac{\frac{dv^*}{dp} - [r-n]}{\sigma}\cdot\frac{dp}{dt}}_{\equiv B\text{: complications}}.$$

A is the composition change due to a noisier signal of true health status, $\frac{d\sigma}{dt} < 0$ and the subsequent change in hospitalizations. Using the result for $\frac{dv^*}{d\sigma}$ under the normality assumption from above, we can show that this mechanism leads to systematically fewer hospitalizations if the initial cutoff is sufficiently large,

$$v^* > (1-p)\,r + pn.$$

B indicates a change in the probability of high risk patients among nursing home residents as treatment time per patient changes; in particular, complications become less likely and the healthy state becomes more frequent with more treatment time, $\frac{dp}{dt} < 0$. This implies a strictly larger share of hospitalizations among nursing home patients because $r > n$ and from equation (5),

$$\frac{dv^*}{dp} = -\frac{\frac{1}{p^2}\frac{c}{\Delta y - c}\gamma\left(\frac{v^*-n}{\sigma}\right)^2}{\frac{1}{\sigma}\gamma'\left(\frac{v^*-r}{\sigma}\right)\gamma\left(\frac{v^*-n}{\sigma}\right) - \frac{1}{\sigma}\gamma\left(\frac{v^*-r}{\sigma}\right)\gamma'\left(\frac{v^*-n}{\sigma}\right)} < 0.$$

Intuitively, for any signal the share of high risk patients has increased and therefore the threshold should be lowered to offer hospital treatment to a larger part of these patients. The relative size of these counteracting effects depends on the underlying model parameters for the distribution of patient types and the cost and benefit structure of hospitalization.

Finally, we combine the previous insights to analyze the overall composition of hospital patients and to characterize changes in patient selection. Using Bayes' theorem, we get

$$Pr\,(r\,|\,v > v^*) = \frac{p\cdot[1-Pr\,(v < v^*\,|\,r)]}{1-Pr\,(v < v^*)}.$$

The change in the share of high risk patients among discharged residents is given by

$$\begin{aligned}\frac{d}{dt}Pr\,(r\,|\,v > v^*) = &\frac{\left[[1-Pr\,(v < v^*\,|\,r)]\,\frac{dp}{dt} - p\cdot\frac{d}{dt}Pr\,(v < v^*\,|\,r)\right][1-Pr\,(v < v^*)]}{Pr\,(v > v^*)^2}\\ &+\frac{\frac{d}{dt}Pr\,(v < v^*)\,p\cdot[1-Pr\,(v < v^*\,|\,r)]}{Pr\,(v > v^*)^2}.\end{aligned}$$

In the data, we find $\frac{d}{dt}Pr\,(v < v^*) \approx 0$, so the risk composition improves in treatment time t if

$$\underbrace{[1-Pr\,(v < v^*\,|\,r)]\,\frac{dp}{dt}}_{\text{change in patient mix}} - \underbrace{p\cdot\frac{d}{dt}Pr\,(v < v^*\,|\,r)}_{\text{change in patient separation}} > 0.$$

Rewriting this condition yields

$$\epsilon_{p,t} > \epsilon_{\sigma,t} \cdot \frac{\frac{v^*-n}{\sigma} \cdot \gamma\left(\frac{v^*-r}{\sigma}\right)}{1-\Gamma\left(\frac{v^*-r}{\sigma}\right)} \Leftrightarrow \frac{\epsilon_{p,t}}{\epsilon_{\sigma,t}} < \frac{v^*-n}{\sigma} \cdot \gamma\left(\frac{v^*-r}{\sigma}\right) < \frac{\frac{v^*-n}{\sigma} \cdot \gamma\left(\frac{v^*-r}{\sigma}\right)}{1-\Gamma\left(\frac{v^*-r}{\sigma}\right)}.$$

Intuitively, the elasticity of the share of sick patients with respect to treatment time has to be sufficiently small compared to the elasticity of signal variance with respect to treatment time. As less treatment time increases the share of high risk types among nursing home residents in general, a larger $\epsilon_{p,t}$ worsens the risk composition among preexisting hospital discharges more. The screening effect according to $\epsilon_{\sigma,t}$ works in the opposite direction through the reduction in signal strength. Lower treatment time leads to noisier signals and a higher share of high risk types who remain in the nursing home. As a result the risk composition among hospital discharges improves. If the ratio of elasticities is sufficiently small, the second effect will dominate and the patient selection in hospitals will improve.

D Details on Mechanisms

D.1 Technology Substitution and Adoption

Figure 21: Angioplastic Substitution Patterns

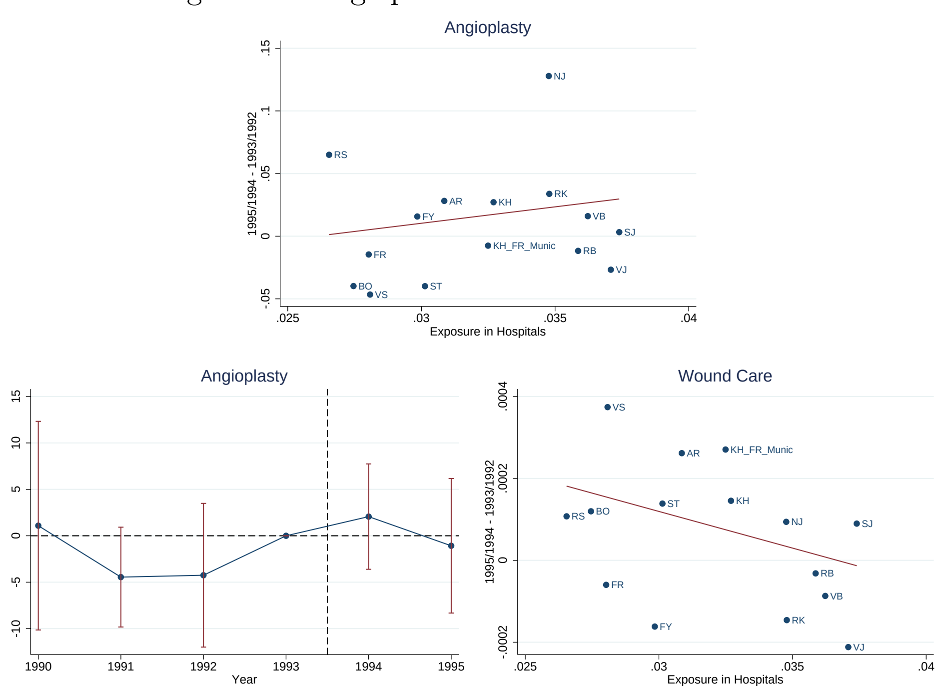
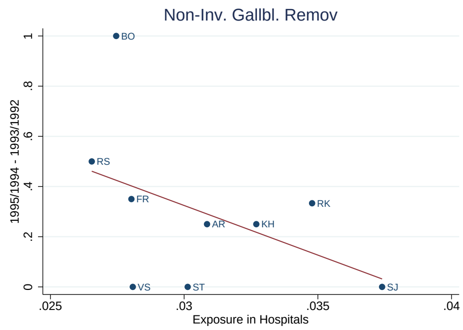


Figure 22: Robustness Technology Adoption



D.2 Hospitalizations of Nursing Home Residents and Mortality

Table 15: Hospitalizations of Nursing Home Residents Ages 85 and older

	(1) All	(2) Last Life Month	(3) Last Life Month: Pneu	(4) Last Life Month: Circ	(5) TTD<1Mo
λ^{post}	-.716	-2.236	-24.933	-7.332**	-1.949**
	[-3.562,2.13]	[-4.995,.522]	[-68.649,18.782]	[-13.562,-1.101]	[-3.721,-.178]
Δ_1	1.034	-.09	-32.26	-4.116	-.457
	[-1.091,3.159]	[-2.07,1.89]	[-70.959,6.439]	[-15.511,7.279]	[-4.855,3.941]
Δ_2	.435	-.711**	-27.334	-3.359	-.136*
	[-7.504,8.374]	[-1.326,-.097]	[-83.999,29.331]	[-11.703,4.985]	[-.284,.012]
Δ_3	.179	-1.619	-20.081	-3.357	-.627
	[-1.952,2.31]	[-3.648,.41]	[-55.656,15.495]	[-8.582,1.869]	[-2.451,1.197]
Pre-Reform Value	.21	.158	.627	.462	.238
Avg. Effect	-.023	-.072	-.802	-.236	-.063

The 95% confidence interval is displayed in brackets.
Standard errors are clustered at the county level. Column 1 presents the effect on overall hospitalizations. Columns 2-4 document the probability of a hospital visit in the last life month, for all residents, and residents dying from pneumonia or ischemic diseases, respectively. Column 5 displays the probability that the time to death is less than one month among hospitalized residents.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

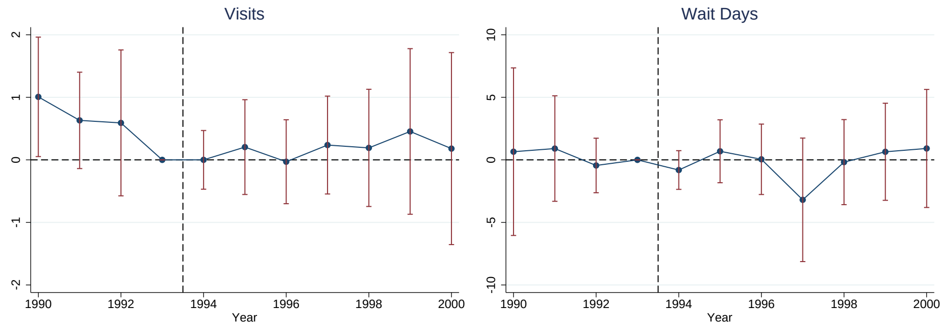
Table 16: Hospitalizations of Nursing Home Residents and Mortality

	(1) Hosp Mortality Jan-Jun	(2) NH Mortality Jan-Jun	(3) Hosp Mortality Jul-Dec	(4) NH Mortality Jul-Dec
λ^{post}	4.489	-2.993*	6.794	4.817**
	[-1.207,10.184]	[-6.312,.326]	[-3.346,16.935]	[.613,9.021]
Δ_1	2.655	.581	3.742	3.573
	[-5.582,10.891]	[-2.171,3.333]	[-8.182,15.666]	[-2.907,10.054]
Δ_2	1.261	.899	7.755	2.488**
	[-3.408,5.929]	[-28.658,30.457]	[-301.678,317.188]	[.275,4.702]
Δ_3	2.485	.039	-.725	4.605***
	[-4.06,9.03]	[-2.474,2.552]	[-9.515,8.065]	[.769,8.442]
Pre-Reform Value	.344	.182	.478	.197
Avg. Effect	.144	-.096	.218	.155

The 95% confidence interval is displayed in brackets.
Standard errors are clustered at the county level..
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$

D.3 Access to Care

Figure 23: Access to Hospital Care



D.4 Patient Selection in Nursing Homes

Figure 24: Nursing Home Patients: Entry and Exit Decisions

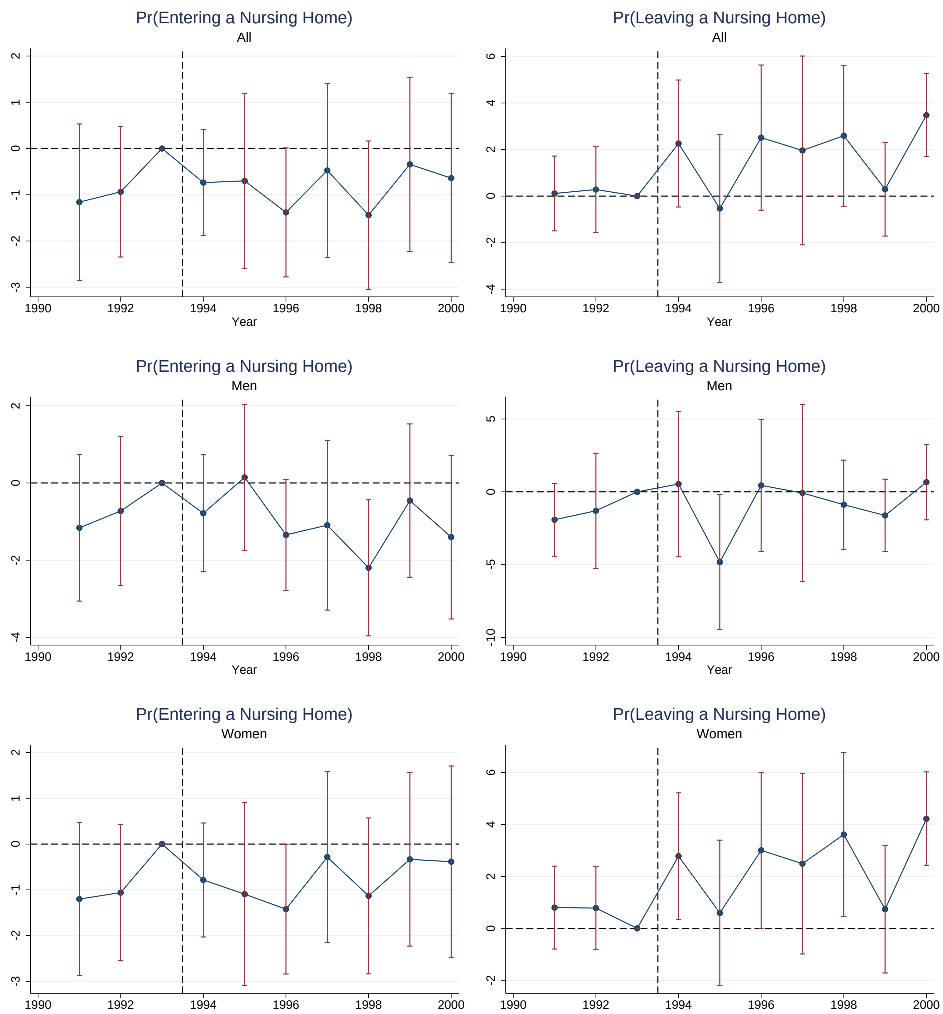


Figure 25: Nursing Home Patients: Entry and Exit Decisions