Health Insurance as Economic Stimulus?
Evidence from Long-Term Care Jobs

Martin Hackmann†  Joerg Heining†  Roman Klimke§  Maria Polyakova¶
Holger Seibert∥

September 16, 2022

Abstract

Arrow (1963) hypothesized that demand-side moral hazard induced by health insurance leads to supply-side expansions in healthcare markets. Capturing these effects empirically has been challenging, as non-marginal insurance expansions are rare and detailed data on healthcare labor and capital is sparse. We combine administrative labor market data with the geographic variation in the rollout of a universal insurance program—the introduction of long-term care (LTC) insurance in Germany in 1995—to document a substantial expansion of the inpatient LTC labor market in response to insurance expansion. A 10 percentage point expansion in the share of insured elderly leads to 0.05 (7%) more inpatient LTC firms and four (13%) more workers per 1,000 elderly in Germany. Wages did not rise, but the quality of newly hired workers declined. We find suggestive evidence of a reduction in old-age mortality. Using a machine learning algorithm, we characterize counterfactual labor market biographies of potential inpatient LTC hires, finding that the reform moved workers into LTC jobs from unemployment and out of the labor force rather than from other sectors of the economy. We estimate that employing these additional workers in LTC is socially efficient if patients value the care provided by these workers at least at 25% of the market price for care. We develop a model of product and labor markets to show—in general—how product market subsidies and labor market frictions may interact. In the spirit of Harberger (1971), when supply-side labor markets do not clear at perfectly competitive wages, subsidies for healthcare consumption along with the associated demand-side moral hazard can be welfare-enhancing.
1 Introduction

Arrow (1963) and Feldstein (1971, 1977) have argued that the rise in healthcare spending and the scope of the healthcare sector are attributable to the growth in demand induced by generous health insurance coverage—or in other words, to moral hazard. These aggregate effects of moral hazard have been difficult to quantify empirically. Most of the recent changes in social insurance programs are marginal expansions that may have fundamentally different, likely much smaller, effects on the healthcare sector (Finkelstein, 2007). Equally sparse is the evidence on the nature and normative implications of these aggregate effects, as the ability to precisely measure how healthcare workers, firms, and capital reallocate in response to insurance expansions is often limited.

In this paper we take advantage of a unique combination of a relatively recent episode of non-marginal social insurance rollout—the introduction of universal long-term care insurance (LTC) in Germany in 1995—and detailed and comprehensive administrative labor market data, to examine how social insurance affects the allocation of health care workers across sectors. Retaining or generating healthcare jobs is a common public policy goal. At the same time, Baicker and Chandra (2012b) argue that thinking about healthcare jobs as the driver of economic growth may be misguided, as these jobs will be inefficient if they do not lead to improvements in patient health and pull workers away from other, more productive, activities. We will argue that, in practice, such a normative assessment depends on the frictions in the incumbent labor markets, as in Harberger (1971).

We proceed in two steps. In the first part of our analysis, we zoom in on the effect of insurance on aggregate employment in inpatient long-term care (SNF for “skilled nursing facilities”), which accounts for the majority of spending in LTC and is one the most labor-intensive parts of the healthcare system. The second part of our analysis goes beyond the partial equilibrium perspective and considers workers who were marginal to the insurance reform. Analyzing these workers’

---

1 An exception is Finkelstein (2007), who has documented a significant expansion in the U.S. hospital sector following the introduction of Medicare in 1965. Her estimates suggest that the increase in spending was more than six times larger than what the estimates from the RAND Health Insurance Experiment would have predicted. This was likely attributable to the high fixed costs of investments in new technologies or capacity, as well as spillover effects. Further, Gottlieb et al. (2020) find evidence of changes in the income and labor supply of physicians in response to the relatively large insurance expansion in 2014 following the Affordable Care Act.
counterfactual employment decisions allows us to assess potential general equilibrium employment spillover effects to other sectors of the economy.

Our baseline research design is similar in spirit to the approach in Finkelstein (2007). We use historical records of means-tested assistance for long-term care services that predated universal coverage for 32% of the population needing care, to construct a measure of the geographic variation in exposure to the national insurance rollout. To characterize the spillover effects to other sectors, we need to contend with the empirical challenge that most individuals in the workforce are not considering career options in LTC and are hence not affected by the hiring efforts of inpatient LTC providers. To zoom in on the relevant population, we draw on recent advances in machine learning techniques to identify and exclude a large fraction of individuals in the broader workforce who had a very low probability of SNF employment. We then apply our research design to the remaining sample of individuals, whom we refer to as the “at risk” (that is, at risk of being hired into SNF employment) population, to infer counterfactual career choices of workers who were marginal to insurance expansion.

Our empirical findings allow us to draw several important conclusions about the relationship between insurance and the supply-side of care. First, we document that the LTC insurance expansion leads to a dramatic increase in the number of firms and workers in this labor-intensive industry. We estimate that a 10 percentage point expansion in the share of insured elderly leads to 0.05 (7%) more inpatient LTC firms and four (13%) more workers per 1,000 elderly in Germany. Scaling this to the aggregate level of expansion that offered insurance to an additional 68% of the population needing long-term care, we find that insurance expansion leads to 0.35 (a 49% increase) more inpatient LTC firms with 30.6 (96%) more workers per 1,000 elderly in Germany. This amounts to an arc-elasticity of healthcare utilization to the price of care of 0.8—significantly larger than the elasticity estimates found in the RAND or the Oregon experiments (Newhouse et al., 1993; Finkelstein et al., 2012), but consistent with the evidence in Finkelstein (2007). The evidence on firm entry supports the idea that fixed costs of investment may be one reason for the differences in elasticity estimates between marginal and non-marginal insurance expansions.

Second, we gain novel insights into the anatomy of how a sector expands in response to the
insurance-induced demand shock. We utilize our ability to observe workers’ full job histories to examine which workers were joining the inpatient LTC sector after the reform, and how wages adjusted to accommodate the large influx of new workers. Perhaps surprisingly, we observe relatively limited movement of wages, which if anything, adjust downward. A textbook model of labor supply and demand would suggest that if firms wanted to hire more workers, they would increase wages unless labor supply is perfectly elastic. Empirically, however, our findings suggest a small reduction in the starting wage among new hires and experienced workers alike. The decline can largely be explained by a change in the skill mix toward less-educated and less-experienced workers, who are disproportionately hired out of unemployment. But even conditional on rich worker observables or worker fixed effects, we still find no evidence for an increase in wages.

Third, we find no conclusive evidence for the existence of negative spillover effects on employment in other sectors of the economy. In the risk sample of individuals who have an increased probability of considering SNF employment, we find a substantial reduction in unemployment that can fully account for our estimated increase in SNF employment. This suggests that—in this particular empirical setting—the marginal SNF hires would have collected unemployment benefits in the absence of insurance expansion.

Fourth, we assess the potential effects on elderly mortality. Our findings point to a reduction in elderly mortality but are unfortunately underpowered to rule out small increases in mortality with high statistical confidence.

To summarize, our findings suggest that the LTC expansion boosted firm entry and career opportunities for lower skilled workers at pre-reform wages, who would otherwise have collected unemployment benefits. In the last part of the analysis, we reconcile these findings through a conceptual framework that also allows us to quantify the welfare effects of expansion using a back-of-the-envelope calculation. First, we argue that collective bargaining, which was pervasive in Germany around the time (Antonczyk et al., 2010; Dustmann et al., 2014) and particularly so in LTC, leads to wage compression and may thereby introduce a wage floor for lower skilled workers. Consistent with this observation, we estimate that potential SNF hires had a reservation wage of only 64% of the going wage. This difference points to large gains in worker surplus from getting
an SNF job and can explain why inpatient LTC providers were able to hire more workers without raising wages, drawing from the excess supply of lower-skilled workers willing to work at the going wage. Second, we incorporate the distortionary effects of unemployment benefits, which equal about 39% of the going wage. Netting these out, we estimate the social cost of employment to be only $64 - 39 = 25\%$ of the going wage among new hires. Combining these estimates, we calculate that LTC insurance expansion increased labor market welfare by up to 576 million EUR per year among new hires, likely exceeding the traditional deadweight loss from moral hazard in the product market.

These findings lead to our main conceptual insights. While the welfare effects of moral hazard are usually thought of as being driven by welfare losses from the inefficient consumption of care, this framework is incomplete if there are frictions in related (input) markets that leave socially efficient trades on the table (Lipsey and Lancaster, 1956; Harberger, 1971; Frick and Chernew, 2009). In our setting, moral hazard leads to the creation of jobs that displace workers from unemployment and pay significantly above reservation wages. More broadly, and in the spirit of the second-best, our findings emphasize that the surplus from the marginal dollar of public funds channeled through an insurance program needs to take into account not only the efficiency loss on the demand side, but also possible efficiency gains on the supply side when price rigidity, regulations, or market power distort healthcare production.

Our analysis is related to several strands in the literature. First we shed new light on the aggregate effects of insurance expansion in the context of long-term care, contributing to the rich literature that has analyzed insurance expansions, mostly in acute inpatient or outpatient healthcare contexts—Finkelstein et al. (2018) provide a relatively recent overview. A distinct feature of our analysis, besides the different setting, is that we can analyze the relocation of factor inputs between sectors that are important for the normative assessments. Our evidence on the allocation of health care workers ties together the discussion on the role of healthcare jobs in the broader economy (Baicker and Chandra, 2012b) and the role of frictions in health labor markets that may come from wage regulations (Sojourner et al., 2015; Propper and Van Reenen, 2010; Friedrich and Hackmann, 2017), monopsony power (Staiger et al., 2010; Prager and Schmitt, 2021), or price regulations and
market power in output markets (Hackmann, 2019).

Our findings also contribute to a literature on personnel economics in LTC. Previous studies have documented that increases in SNF staffing generally lead to improvements in patient health (Lin, 2014; Stevens et al., 2015; Antwi and Bowblis, 2018) and that staffing ratios may even be inefficiently low (Friedrich and Hackmann, 2017; Hackmann, 2019). As such, a large literature has focused on policies that may give providers incentives to increase staffing ratios, including minimum staffing ratios (Lin, 2014; Chen and Grabowski, 2015), increases in provider prices (Hackmann, 2019), or making information about quality public (Werner et al., 2012; Grabowski and Town, 2011). Our findings suggest that collective bargaining may distort employment of lower-skilled workers downward, completing evidence from Friedrich and Hackmann (2017), who analyze the consequences of a policy-induced shortage among high-skilled nurses.

Last, our analysis relates to a broader literature on labor market frictions and their policy implications for lower-skilled workers. Collective bargaining and wage compression were pervasive throughout the German labor market in the mid-1990s and may have contributed to high unemployment rates for lower-skilled workers in the broader economy (Antonczyk et al., 2010; Dustmann et al., 2014). Our analysis provides a clean case study for this relationship. Conceptually, the wage floor induced by wage compression operates as a minimum wage, and as such, our findings contribute to the vast and influential literature on the role of minimum wages in the economy—see, e.g., Cengiz et al. (2019) for recent estimates and Manning (2021) for a recent overview. The employment consequences of minimum wages depend on whether low-wage labor markets are best characterized as highly competitive, or not, and of course on the magnitude of the minimum wage. These factors contribute to different estimates across different settings. An advantage of our setting is that we can speak to the overall employment effects in addition to the industry effects. Such overall employment effects have received much less attention in the minimum wage literature. Our findings point to a high wage floor, suggesting that labor demand as opposed to labor supply is the binding market side. As such, our setting predicts that supply-side expansions have little effect on wages and instead contribute to unemployment, which is consistent with the evidence on older workers in Germany in response to immigration shocks, as shown in Dustmann et al. (2017).
The rest of the paper proceeds as follows: In Section 2, we discuss the economic environment and data. Section 3 outlines our empirical strategy. In Section 4, we discuss empirical results. Section 5 outlines a simple model of labor demand and supply in long-term care and derives implications of our findings for assessing the normative impact of moral hazard. Section 6 offers a brief conclusion.

2 Data

2.1 Institutional Primer

This subsection summarizes key institutional details around the introduction of universal long-term care (LTC) insurance in Germany in 1995–1996. For more details, see Rothgang (1997); Nadash et al. (2018). Throughout, we focus on inpatient long-term care, often provided in skilled nursing facilities (SNF). SNFs account for the largest share of the LTC workforce and spending, and we can best identify these firms and their workers in our data.2

Prior to 1995, the German welfare system offered only means-tested financial support for inpatient and outpatient (Pabst, 2002) LTC services—Hilfe zur Pflege3 (HzP). LTC providers were reimbursed from state and municipal budgets for care provided to indigent elderly patients on a cost basis.4 Providers were predominantly public and not-for-profit, typically owned by Catholic (Caritas) or Protestant (Diakonie) churches or nonstatutory welfare agencies, jointly accounting for about 84% of inpatient beds in 1992.5 Regulatory entry barriers made it difficult for private providers to receive reimbursements through HzP.6 The fact that public and not-for-profit firms dominated the SNF market is important, as the vast majority of public and not-for-profit providers have historically set (and continue to do so today) wages through collective bargaining agreements. These agreements typically result in wage compression and wages that significantly exceed market wages, particularly so for lower-skilled workers.7 In Section 5, we will come back to the role of

2See, e.g., Figure 3 in shorturl.at/cmCDT, last accessed in September 2021, for an overview of the share of LTC spending allocated toward inpatient care across OECD countries. Furthermore, most long-term care workers practice in residential care settings (Colombo et al., 2011).
3Help for Care.
4According to Rothgang (1997), p. 44, inpatient care providers were assured that their costs of care provision would be reimbursed from state and municipal budgets.
5See Table 4 in Rothgang (1997).
7Estimates from Bispinck et al. (2013) suggest that employees in nursing-related occupations earn 20% less if their
wage-setting frictions.

In an effort to reduce the financial burden on local budgets and to meet the growing demand for LTC services in a rapidly aging population, Germany passed sweeping LTC reform in 1994, which became effective in 1995–1996. The new social insurance for long-term care was not means-tested and offered flat-rate benefits for any individual for whom long-term care was deemed medically necessary. The program was funded on a pay-as-you-go basis through mandated payroll contributions earmarked for LTC.\textsuperscript{8}

The new benefits covered inpatient and outpatient LTC, were independent of an individual’s income and assets, and increased with the individual’s level of disability, which was determined by independent assessors. For inpatient care, the benefits intended to cover the costs for healthcare services and the investment component of SNF care, requiring patients to pay for the room-and-board component out of pocket. In practice, the new insurance provided a fixed subsidy, and patients paid the difference between the subsidy and the market price, which was negotiated between the LTC provider and the insurer. The implicit patient cost-sharing was around 43% in the early years of the program and increased to around 54% by 2010.\textsuperscript{9}

The sweeping expansion of benefits to the entire population has diminished the role of HzP as a source of revenue for providers and more than tripled the total amount of public spending on LTC. (See Figure 1A). Coverage rollout has led to a dramatic growth of the LTC sector in Germany, according to contemporary market observers and government reports alike (Bundesministerium für Arbeit und Soziales, 1997; Rothgang, 1997).\textsuperscript{10}

\textsuperscript{8}Originally, contribution rates equaled 1.7\% of income up to the monthly cap of 4,237.50 EUR, and were gradually increased to 2.55\% in 2017.

\textsuperscript{9}In 1999, market prices for patients with the highest but also the most common care needs equaled 65 EUR per patient per day for healthcare services, and another 18 EUR per patient per day for room and board. LTC insurance offered patients with these needs financial support of 2,800 Deutsche marks per month, which corresponds to roughly 1,400 EUR per month, or 1,400 / 30 = 47 EUR per day. This implies an out-of-pocket pay of about 65 + 18 - 47 = 36 EUR per patient per day, which corresponds to 43\% of the market price. Herr et al. (2016) report an average out-of-pocket price of 1,685 EUR per month between 2007 and 2009 for the highest level of care. During the same time window, the monthly insurer contributions paid to an SNF for beneficiaries of the highest-care level equaled 1,432 EUR. This implies a patient cost-sharing rate of about 1,685 / (1,685 + 1,432) = 54\%. In 2010, Grant et al. (2019) report a total price of 109 EUR and a subsidy of 50 EUR per day among patients at the highest care level.

\textsuperscript{10}The diminished importance of HzP as a revenue source has also led to a leveling in the playing field between private, public, and not-for-profit providers.
2.2 Population

Our primary source of data is the Integrated Employment Biographies (IEB) database provided by the German Institute for Employment Research, which is based on the process-generated data of the German Federal Employment Agency.\textsuperscript{11} IEB is the universe of employment spells for the universe of workers subject to social security contributions in Germany from 1975 to 2019.\textsuperscript{12} We aggregate the raw spell–level data to the individual-year level by retaining the spell that is observed on June 30 of each year.\textsuperscript{13} We drop individual-year observations for employment in (former) East Germany, Berlin, or Bremen, for which no consistent time series are available. Appendix B.1 provides more detail on data processing.

We construct two analytic samples from the resulting database. The first extract (“SNF Sample”) selects full labor market biographies for individuals who were employed in a skilled nursing facility (SNF)\textsuperscript{14} at least once\textsuperscript{15} between 1975 and 2008. We exclude observations from 2009 onward due to substantial changes in the industry classification system (Eberle et al., 2011).

The second extract (“Labor Market Sample”) starts with a 10% random sample of all labor market histories. We use this sample to identify potential new hires into SNF based on their last five years of labor market history, as we discuss in more detail below. We retain worker-year observations for when individuals are at least 25 years old, for whom we can observe at least five years of labor market history, and who were not employed in an SNF five years prior to year \( t \). This retains individuals employed in any sector of the economy, or unemployed, or out of the (West German) labor force. Since we require a lookback period of five years, this sample only keeps observations from year 1980 onward. We stop the sample in year 2004 because of changes in the data.

\textsuperscript{11}IEB database are processed and kept by the Institute for Employment Research according to Social Code III. The data fall under the confidentiality regulations of the German Social Code (Book I, Section 35, Paragraph 1). Access to the data is regulated by Section 75 of the the German Social Code, Book X.

\textsuperscript{12}Specifically, the IEB data consist of all individuals in Germany, who fall into one of the following employment categories: employment subject to social security (in the data since 1975), marginal part-time employment (in the data since 1999), benefit receipt according to the German Social Code III (since 1975) or II (since 2005), officially registered as job-seeking at the German Federal Employment Agency or (planned) participation in programs of active labor-market policies (in the data since 2000).

\textsuperscript{13}We first clean the spell-level observations, following (Eberle and Schmucker, 2019).

\textsuperscript{14}SNF is defined as an establishment with WZ73 industry codes for private and for-profit institutions or “homes” (710), private and not-for-profit homes (711), and homes in public ownership (712). The private not-for-profit institutions are primarily owned by social service organizations of Catholic and Protestant churches. We use time-consistent industry codes, following the procedure of Eberle et al. (2011).

\textsuperscript{15}We only consider “regular” employment, following the IAB convention—see Appendix B.2 for details.
recording of the long-term unemployment spells (Antoni et al., 2019) that are important for our analysis.

2.3 Characteristics of Workers

We observe the date of birth, sex, nationality, and educational attainment for individuals in our sample. For employment episodes, we further observe the anonymized employer identifier, employer's industry code, geographic location (county) of the employer, whether employment was full-time or part-time, and the employee's average daily wage. See Appendix B.2 for additional information on these variables.

In addition, we construct two measures of labor market experience for each individual from the (annualized) employment-spell data. First, for each year $t$, we compute the number of years the individual was employed in years $t - 15$ to $t - 1$. Analogously, we compute the number of years the individual worked in an SNF establishment in years $t - 15$ to $t - 1$.

Finally, we classify worker-year observations of SNF employment spells into SNF incumbents and new hires. A hire is defined to be new in year $t$ if an individual is employed in an SNF in year $t$ but not in year $t - 1$.

2.4 Mortality

We use two sources of mortality data. First, we compute county-level mortality rates for individuals aged 75 and older from the vital statistics of each West German state except Bremen and Rhineland-Palatinate (because of missing data). These data are available from 1991 to 2017 (Statistische Ämter des Bundes und der Länder, 2021b). The second source is the Human Mortality Database, which allows us to compute age-by-sex mortality for years 1991–2008 for the former West Germany and 28 other countries.

---

16Mortality data for years 1991–1994 have been obtained through written requests directed to the statistical offices of the respective German federal states.
2.5 Means-Tested LTC Benefits

We use historical statistical reports to compute the number of individuals who were covered by means-tested HzP in 1993. The counts of HzP recipients were available for 15 geographic regions covering the territory of the former West Germany. This includes state-level observations for all states except Bavaria. For Bavaria, we observed recipient counts for seven substate regions (Regierungsbezirke).\(^{17}\)

To construct the reform exposure variable in Section 3, we further use counts of LTC claims in 1999, the first year for which reliable statistics on LTC claims by local geography are available. These were obtained from LTC insurance statistics published by the Federal Statistical Office of Germany (Statistisches Bundesamt, 1999).\(^{18}\)

2.6 Descriptive Statistics

Table 1 provides descriptive statistics for the two analytic samples. The “SNF Sample” summarized in column (1) consists of 24.3 million observations for 1.6 million unique workers over the course of 1975 to 2008. Individuals in the sample are on average 38 years old. Some 77% are female, and 94% are German nationals. About 10% of the workers had completed the upper tier of high school (Abitur).\(^{19}\) Some 61% of observations are for employment in the healthcare sector, while 10% are unemployment episodes. The employment spells span nearly a million unique establishments of any kind and 18,675 SNF establishments. SNF spells, summarized in column (2), account for 9.8 million observations, or 40%, for the workers in our sample. During SNF employment episodes, workers are on average slightly older—41 years of age—and slightly more female, at 81%.

SNF employment episodes tend to happen later in a worker’s career and are more likely to be part-time (27% of all employment spells, vs. 33% for SNF spells). During SNF episodes,

\(^{17}\)Counts of recipients of Hilfe zur Pflege at the state level were obtained from Statistisches Bundesamt (1993, p. 96). Counts for Bavaria at the regional level were obtained from page 297 of the volume Regionalbericht 1993, published by the Statistical Office of Bavaria (Statistical Office of Bavaria, 1993).

\(^{18}\)Counts of LTC insurance beneficiaries in Bavaria in 1999 were obtained from the Statistical Office of Bavaria’s GENESIS website at www.statistik.bayern.de.

\(^{19}\)Our data is representative of the national Abitur rates for the cohorts that we consider. For example, among 762,026 individuals graduating from high school in West Germany in 1970, 87,882 (= 11.5%) graduated with Abitur. These individuals were of prime working age by the time universal LTC insurance was introduced (Statistisches Bundesamt, 1995, Page 53).
workers have about four months more of labor market experience and 2.4 years more of SNF-specific experience. Workers earn 6% higher wages during their SNF spells (78 EUR/day vs. 83 EUR/day, in 2020 Euros). About 59% of SNF employment episodes are in not-for-profit (mainly church-owned) SNFs, 27% in for-profit, and 14% in publicly owned institutions.

Column (3) summarizes our “Labor Market Sample,” which has 48 million observations for 3.8 million individuals over the 1980–2004 period. Subject to the sample refinements discussed earlier, this sample is broadly representative of the German workforce aged 25 and older. Individuals are on average 41 years old, 41% are female, and 92% are German nationals. These workers are about 10 times less likely to be employed in the healthcare sector (6%), and 2 percentage points less likely to be unemployed at any point in time (6.7%) than the workers in the SNF Sample. The average worker in the Labor Market Sample is also less likely to be working part-time (12%, vs. 27% part-time) and earns 32% higher wages.

In sum, we observe that an individual who, at some point in his or her career, works in an SNF (column 1) is 87% more likely to be a woman, 43% more likely to experience an unemployment spell, more than twice as likely to work part-time, and earns substantially lower wages relative to an average worker in Germany who is aged 25 or older (column 3).

3 Research Design

3.1 Geographic Variation in Exposure

Our main empirical strategy relies on the geographic variation in the pre-reform coverage rates through the means-tested HzP program. The introduction of universal LTC insurance meant that all geographic areas had coverage for all people with medically approved LTC needs following the 1995–1996 rollout. However, regions with lower pre-reform HzP coverage were in practice more affected by the expansion.

To capture this geographic variation in exposure, we use data on the number of claimants of LTC needs are determined by independent assessors (primarily doctors and nurses) who have no financial incentive to approve or deny applications. According to Nadash et al. (2018), benefit determinations, including denials, have generally been accepted as reliable and fair, and, if appealed, are rarely overturned.
HzP in 1993 and an estimate of the total underlying demand for care in the same year. We define exposure measure $E_r$ as follows:

$$E_r = 100\% - \frac{HzP_{r,1993}}{g_{r,1993,1999} \times LTCClaims_{r,1999}},$$

(1)

where $r$ denotes one of 15 regions for which we observe the count of HzP claimants in 1993, denoted with $HzP_{r,1993}$. $LTCClaims_{r,1999}$ is the region-specific count of all beneficiaries of LTC insurance in 1999. This specification assumes that after the full rollout of LTC insurance, the number of individuals claiming LTC insurance is a good approximation for the true underlying demand. To account for the potential of differential trends in aging across areas between 1993 and 1999, we deflate the 1999 count of LTC demand by the change in the number of older individuals in each region $r$ between 1993 and 1999. The deflation factor $g_{r,1993,1999} = \frac{OlderPop_{r,1993}}{OlderPop_{r,1999}}$ is the region-specific ratio of age 65+ population in 1993 to that in 1999. Intuitively, $E_r$ measures the share of individuals needing long-term care who did not have insurance coverage for this care prior to the reform.

Using this source of variation, we estimate an event study specification that measures whether areas that were more exposed to the national insurance reform experienced differential changes in the outcomes of interest. The identifying assumption needed for the causal interpretation of our estimates is that, in the absence of the insurance rollout, outcomes would have grown in parallel across geographic areas with different levels of exposure to LTC insurance expansion. For an outcome $Y_{c(r)t}$ in county $c$ within region $r$ in year $t$, we estimate:

$$Y_{c(r)t} = \alpha_c \times 1(\text{county}_c) + \delta_t \times 1(\text{year}_t) + \sum_{t=1975}^{t=2008} \lambda_t \times (E_r) \times 1(\text{year}_t) + \epsilon_{c(r)t}$$

(2)

To simplify the exposition, we also report estimates from a difference-in-differences specification.
that pools coefficients of transition years 1994 to 1996, and post-reform years 1997 to 2008:

\[
Y_{c(r)t} = \alpha_c \times 1(\text{county}_c) + \gamma_t \times 1(\text{year}_t) + \sum_{t=1975}^{t=1992} \delta_t \times (E_r) \times 1(\text{year}_t) \\
+ \delta_{94-96} \times (E_r) \times 1(\text{year}_{94-96}) \\
+ \delta_{97-08} \times (E_r) \times 1(\text{year}_{97-08}) + \epsilon_{c(r)t}
\]

(3)

We consider four sets of outcomes \(Y_{c(r)t}\): 1) the number of SNF firms and workers, 2) workers’ income, 3) the demographic characteristics of newly hired workers and their labor market experience, and 4) mortality. We aggregate outcomes to the county-year level by either summing (in the case of counts) or taking an average (in the case of characteristics of workers). For the specifications with income as an outcome, we first residualize log-wages, taking out the variation due to labor market experience (for new hires) or individual fixed effects (for incumbents). To account for the differential size of counties and for the potential for differential aging trends across geographies, we use population counts of individuals aged 65 and above to scale the count-based outcome measures into per elderly capita terms.

### 3.2 Counterfactual Careers

To characterize the potential spillover effects of the LTC insurance expansion on other sectors of the economy, we investigate the career choices at the population level. We are interested in counterfactual career paths of individuals in the SNF hiring pool. A practical challenge is that a large fraction of the workforce never considers career opportunities in LTC, either before or after LTC coverage expansion. This makes it difficult to quantify the causal effect of the LTC expansion at the workforce level.

To overcome this challenge, we use machine learning techniques to identify individuals with a nonzero probability of being hired into an SNF in the Labor Market Sample, as described in Section 2. We estimate a CART regression-tree model where the binary outcome is SNF employment in period \(t\). As predictors, we use age, sex, nationality, education, and labor market information from five years ago, \(t - 5\). We characterize employment with an industry code (the first two digits
of the industry classification\textsuperscript{21}, and the two-digit occupation code based on the classification of occupations recorded in our data (KldB1988 system). We include a separate indicator for being unemployed.

We train the prediction model on the data spanning five years before and after the reform, 1990–2000. To mitigate the over-fitting concerns, we choose the complexity parameter that maximizes an out-of-sample $R^2$ through fivefold cross-validation.\textsuperscript{22} We use the CART estimates to predict the probability of being hired into SNF for each individual in our sample. We then keep the pool of potential SNF hires, defining them as individuals with a predicted SNF hiring risk of at least 1%. Appendix Section C provides more details on the estimation procedure.

3.3 Variation in Mortality Across Countries

For the analysis of mortality among individuals aged 75 and older, we supplement the event study in Equation 2 that uses geographic variation in exposure to the LTC reform within Germany, with analyses based on cross-country variation and the synthetic control method (Abadie et al., 2010).

We use the donor pool of the age-75-and-older population’s annual mortality time series in 28 other countries to construct the counterfactual time series for West Germany. We follow Abadie et al. (2010) for the permutation-based inference procedures.

4 Results

4.1 Aggregate Response to Demand Shock

Figure 1 displays the raw time series of the number of SNF workers between 1975 and 2008, both in absolute terms (panel B) and per 1,000 individuals aged 65 and older (panel C). Two descriptive facts are evident from these figures. First, employment in long-term care generally saw persistent growth over the three decades that we study. The number of SNF workers more than quadrupled from 1975 to 2008 (for comparison, population growth in West Germany was 7.5% over the same

\textsuperscript{21}As in our primary analysis, we use the WZ73 industry classification system.

\textsuperscript{22}The complexity parameter is the minimum $R^2$ that every additional leaf on the regression tree must add to be included in the regression tree. Therefore, a smaller complexity parameter yields a more complex regression tree.
time period, according to the Human Mortality Database). Second, this increase was not mainly
driven by the growth in the older population—which was itself pronounced, as we see in Panel
D—but by a substantial increase in the number of SNF workers per elderly capita. The number
of SNF workers per 1,000 individuals aged 65 and older more than tripled, going from 11 to 35
workers per 1,000 elderly.

In Panels A and B of Figure 2, we plot the county-year level data for SNF establishments and
workers separately for the set of counties that were in geographic areas with above (blue line) and
below (red dashed line) median exposure ($E_r$ as derived in 1). We plot the average outcome within
each group of counties. The time series are normalized to the mean of SNF establishments (in
Panel A) or workers (in Panel 2) per capita across all counties in 1993. In the post–insurance
rollout years, shaded in grey, both the number of establishments and the number of workers per
1,000 elderly were growing faster in the counties that were more exposed to insurance expansion.

In Panels C and D of Figure 2, we report the results of estimating the event study in Equation
2. The estimates suggest that prior to 1995, the rate of growth in the number of establishments
and the number of workers per 1,000 elderly did not differ across geographic areas with different
levels of means-tested coverage in 1993. After the rollout of universal insurance, however, we find
that growth was more pronounced in areas that were more exposed to LTC insurance expansion.
The acceleration flattened out around eight years after the new insurance was signed into law.

The pooled difference-in-difference coefficients in Table 2 measure the implied impact of the
reform in an average post-reform year. Our estimates in columns (1) and (2) imply that, on
average, 10 percentage points (or 15% relative to the mean) more exposure to the reform leads to
0.05 (6.4%) more SNFs and 4.5 (14%) more SNF workers at a point in time. The magnitude of the
increase of workers was roughly equally split between part-time and full-time workers (columns C
and D), implying a larger relative effect for part-time workers, of whom there were far fewer prior
to the policy change (nine part-time workers per 1,000 elderly in 1993, versus 23 full-time workers).

A 10 percentage point change in exposure is close to the difference in mean exposure between
counties with above median exposure and below median exposure (0.09), which we refer to as “in-
sample variation” in the third panel of Table 2. Multiplying these “in-sample” per capita effects

16
by the count of individuals aged 65 and older in West Germany (excluding Berlin and Bremen),
we get that the insurance rollout added 450 SNFs and 39,214 SNF workers for each 9 percent of
uninsured elderly. We also compute a more out-of-sample estimate of the aggregate impact of LTC
insurance. Assuming that the effect scales approximately linearly with the share of the ex ante
uninsured implies that expanding universal coverage to 68.6% of the population was responsible
for 0.35 (or 45% relative to the mean of 0.77 in 1993) more SNFs per 1,000 elderly and a nearly
doubling of the SNF workforce.

To put the employment effects into further perspective, we divide the extrapolated increase in
employment by the implicit change in the out-of-pocket prices for an average consumer:

$$\epsilon_{arc} = \frac{\Delta Q/(Q1 + Q2)}{\Delta P/(P1 + P2)} = \frac{30.5/(32 + 62.5)}{68.8\% \cdot 57\%/ (68.8\% \cdot 100\% + 68.8\% \cdot 43\%)} = 0.81 .$$

The numerator considers changes in employment per 1,000 elderly (+30.5 workers) relative to pre-
reform employment (32 workers) and post-reform employment (32+30.5)—see column (2) in Table
2. The denominator considers the change in prices. Pre-reform, 68.6% of potential patients paid
the full price out-of-pocket, the remaining 31.4% were fully insured through means-tested HsP.
So the average out-of-pocket price was 0.686P_{market}. Post-reform, the cost-sharing of the newly
insured, drops to 43%. The new average out-of-pocket price then becomes 0.686 \cdot 0.43 P_{market}. The
effective change in the average price is then 68.6\% \cdot (43\% - 100\%). Put together, this suggests an
arc elasticity of 0.81, which significantly exceeds the elasticity found in the RAND or the Oregon
experiments (Newhouse et al., 1993; Finkelstein et al., 2012). Our data on firm entry provide
evidence that fixed costs of investment may be one reason for the differences in the estimates
(Finkelstein, 2007).

In the Appendix, we report versions of our baseline specifications with county-specific time
trends, alternative clustering of standard errors (Figure A.5 and Table A1), with other ways of
constructing the exposure measure (Figures A.6 and A.7, Table A2), and with controls for geo-
graphic trends in aging (Figure A.8 and Table A3). Our results remain largely invariant to these
alternative specifications.
4.2 Anatomy of Expansion

In this section we characterize the nature of the LTC sector expansion. We consider changes in income and composition of newly hired SNF workers.

4.2.1 Price effects

We start by examining whether the large expansion of the SNF workforce was accompanied by a growth in wages. We expect that firms have to increase their starting wages in order to attract more new hires. Table 3 displays the results from estimating specifications 2 and 3 for logged daily wages of new full-time hires (columns 1 and 2) and of incumbent full-time workers (columns 3 and 4). We find no evidence of systematic changes in wages on average, for either new hires or incumbents. If anything, our findings suggest a small reduction in wages following the expansion. The point estimates become smaller in magnitude as we control for experience (column 2) or worker fixed effects (column 4), suggesting that part of the potential decline can be attributed to a shift towards lower-skilled workers.\(^\text{23}\) The lack of an increase in wages in a rapidly expanding sector points to the existence of wage frictions. The empirical pattern we see is consistent with a labor market equilibrium where the going wage is substantially above the market rate, allowing firms to easily expand their hiring without changing their posted wages. We return to the discussion of potential sources for SNF market wage frictions in Section 5.

4.2.2 Compositional effects

We next consider whether the reform changed the average demographics or qualifications of newly hired SNF workers. Table 4 documents how the expansion of the LTC market changed the characteristics of new workers hired by SNF firms. We find no changes in age, nationality, or sex of the new hires. We do find that an average new hire, post-reform, appears to be less skilled. The new hires are 1 percentage point less likely (11% relative to the mean of 9%) to have the most advanced high school degree for each 9 percentage points of “in-sample” variation in exposure. They also

\(^{23}\)We residualize individual-level log wages to experience or worker fixed effects before constructing county-year level averages.
have less general labor market experience—four months less general labor market experience relative to the average experience of 4.7 years. The point estimates for the SNF-specific labor market experience and for having worked in the healthcare sector previously are noisy, but they point in the direction of less experience. The post-reform new hires are substantially more likely to have been unemployed in the year prior to the SNF hire. Insurance expansion thus had a significant positive effect on hiring out of unemployment, increasing the share of new full-time employees who were not employed before starting an inpatient LTC job from a base of 18% in 1993 by 1 percentage point for each 9 percentage points of additional exposure to the reform. Overall, we conclude that the expansion of the LTC sector resulted in SNF firms moving down in the skill distribution and offering jobs to workers who likely had a harder time finding employment previously.

4.3 New Hires in General Equilibrium

The analysis in the previous section examined how the skill mix of new realized SNF hires changed as a result of the reform. We now ask how the expansion of the SNF sector affected the labor market biographies of the pool of potential SNF hires. Analyzing the pool of potential hires allows us to directly measure the spillover effects of the SNF expansion on other sectors of the economy. We are able to document which other economic activities individuals with an increased hiring probability into SNF would have pursued in the counterfactual without the LTC reform.

4.3.1 Characteristics of potential SNF hires

Table 6 presents the means of the five-year-lagged predictors used in regression tree analysis outlined in Section 3.2. Column (1) replicates the (five-year-lagged) summary statistics for the full Labor Market Sample, which we also summarized in column (3) of Table 1.

We focus our analysis on individuals with a SNF hiring risk of at least 1%, whose characteristics are summarized in column (5). First, we note that only 12.3% of our Labor Market Sample have a meaningful SNF hiring probability. The “at risk” sample of potential hires in column (5) retains 5.9 million out of 48.1 million observations. At the same time, we maintain about 58.2% of the number
of individuals actually working in inpatient LTC. As a result, the sample share of individuals employed in inpatient LTC in period $t$ increases by about fivefold, from 0.56% to 2.65%, as we move from column (1) to column (5), increasing the predicted hiring risk cutoffs. In terms of demographics, the “at risk” sample is skewed toward slightly younger, female, German, and less-educated individuals. These patterns are qualitatively similar to the general differences between an average worker in the economy and an SNF worker, as we discussed in Table 1.

The comparison of the last two predictor means suggests that LTC providers largely recruit workers from unemployment as well as other healthcare sectors. The fraction of workers who were formerly employed in the medical sector increases threefold, from 5.5% to 16%, as we move from the general labor market sample to the “at risk” SNF hiring sample in column (5). Likewise, the fraction of formerly unemployed workers increases threefold, from 4.3% to 14.1%.

### 4.3.2 Employment Effects

Next, we investigate whether and to what extent the two different hiring channels—1) unemployment and 2) other medical sectors—relate to the labor demand shocks induced by the LTC reform. To this end, we estimate regression models (2) and (3) on the sample of potential new hires with hiring risk of at least 1%. Table 7 presents the results.

**SNF employment:** The first column presents the effects on SNF employment in period $t$. Consistent with our earlier evidence, we find that the LTC reform led to a significant increase in SNF employment in our “at risk” sample. A 9 percentage point increase in exposure increases the probability of SNF employment in 5 years’ time by 0.24 percentage points or 9.3% on average.

To connect the findings from the “at risk” sample to the aggregate employment analysis, which uses a longer post-reform time window, we focus on the five-year effects on employment. Scaling the point estimate of 2.5% with a 9 percentage point exposure and by the baseline population in the “at risk” sample in 1993 of 276,795 individuals, we estimate an increase in hiring of 623 workers in the 10% sample, or 6,200 workers in the implied 100% sample. In the aggregate analysis, presented in Table 2, the five-year estimate points to an employment increase of 37,600 workers. We note

\[ \frac{0.0265 \times 5,912,840}{0.0056 \times 48,106,142} = 58.2\% \] of the workers employed in SNF in period $t$. 


24

We maintain
three important differences between the specifications here and those in Sections 4.1 and 4.2 which
contribute to the difference in the point estimates. First, the evidence from the analysis of “at
risk” workers corresponds to estimated changes in new employment flows, whereas the aggregate
evidence points to changes in employment stocks. Scaling the flow estimate of 6,200 workers by five
years would increase the potential cumulative employment gains to 31,000 workers. Second, the
analysis of “at risk” workers does not consider potential retention efforts of firms that may have
contributed to larger employment stocks. And third, the risk analysis only accounts for 58.2% of
new hires.

Employment spillovers: Columns (2) and (3) of Table 7 show the corresponding employment
effects for hospital employment and employment in other healthcare sectors. We find no con-
clusive evidence for changes in these outcomes. The pooled effects are negative but statistically
insignificant. While employment in the healthcare sector is an important predictor of future SNF
employment (see Table 6), the evidence presented here suggests that these sector switches are not
systematically affected by the long-term care reform and may instead be a result of independent
career considerations. That means that LTC insurance expansion had no systematic net employ-
ment effects on these sectors. This observation is also consistent with the evidence from Table 4,
which suggests that new hires, induced by the reform, are less likely to have accumulated labor
market experience (column [5]) and to have worked in the healthcare sector in the past (column
[7]).

Instead, the former evidence suggests that that the marginal workers are disproportionately
hired out of unemployment. Consistent with this, the evidence from column (4) in Table 7 points
to a significant reduction in the probability of being unemployed among individuals “at risk” of
being hired by an SNF following the LTC reform. The reduction can fully account for the increase
in SNF employment documented in column (1). Together, this suggests that new hires in inpatient
LTC would have collected unemployment benefits absent the LTC insurance expansion.

Overall, we conclude that the LTC sector expanded by means of hiring (marginal) individuals
who were formerly unemployed, in effect creating new employment opportunities, rather than
diverting employees from potentially lucrative employment in other healthcare sectors.
4.4 Mortality

We close this section with the analysis of mortality, asking whether the LTC insurance expansion and the associated increase in the SNF labor force lead to a change in health among the elderly. The net effect on mortality is unclear, ex ante. We may expect that better access to formal care will improve health and prolong survival. On the other hand, being cared for outside of the familiar home environment and the lower average skill of new SNF hires may lead to a decline in health.

Figure 3 and Table 5 report the results of estimating the effects of the reform on mortality using the geographic variation in reform exposure within Germany (Panel A in Figure 3 and column (1) in Table 5) as well as the synthetic control method and mortality data from other countries (Panel B in Figure 3 and column (2) in Table 5). In both cases, the analysis lacks statistical power, making us unable to reject a zero net effect on mortality in the age 75+ group. The point estimates and the visual evidence in Figure 3 are suggestive of a potential decline in mortality, with an increasingly more pronounced negative effect on mortality over time. We conclude that the expansion of the SNF sector and increased hiring of observationally lower-skilled workers does not appear to have worsened mortality in the elderly population, and we see suggestive evidence that mortality may in fact have declined.

5 Mechanisms and Welfare

We reconcile our empirical findings through a general equilibrium model of labor and product markets. To model the labor market equilibrium, we closely follow the directed search and matching literature, building on Acemoglu and Shimer (1999) and Wright et al. (2021). In our application we focus on frictions in the labor market as a source of inefficiency that may interact with the introduction of product-subsidies. The general insights, however, go beyond our specific institutional setting and can be used to analyze product-market subsidies in the presence of other frictions in input markets.
5.1 Frictions in the Labor Market

Collective bargaining agreements have traditionally played an important role in the German labor market (Dustmann et al., 2014). While the long-term care sector has not had a sector-specific collective bargaining agreement, in practice in 1990s public and not-for-profit long-term care providers tended to fall under pan-sectoral bargaining agreements. Survey data from 2011 suggest that 80.6% of public and not-for-profit SNF providers set wages via collective bargaining agreements.25

Publicly owned inpatient long-term care providers largely followed wage tables for the public sector. These wages apply to all workers in the public sector; in some years, special wage tables for the nursing occupations were negotiated. The wage tables typically varied by age of the worker, with additional differences in allowances across geographies. There were no explicit bargaining agreements guiding the wage setting of the not-for-profit providers. Most of the not-for-profit provider were owned by Catholic and Protestant Churches in Germany (Church ownership is common in healthcare in Germany). Contemporary accounts of the long-term care labor market suggest that in practice, Church-owned providers tended to follow the public sector wage tables. Privately owned for-profit nursing homes were not constrained in their wage-setting. These institutional facts imply that about three quarters of SNF workers were subject to wage floors from collective bargaining agreements.

Figure 4 presents empirical evidence on wage distributions from our data that is consistent with these institutional facts. In Panel A we plot—for each ownership type—the median, 75th, and 25th percentile of the log daily wage, by years of work experience, among full-time nursing assistants in 1993. In Panel B, for each ownership type, we compute the share of full-time nursing assistant employees at each level of work experience in healthcare. As we do not observe the skill of each worker directly, we use the amount of experience in healthcare as a proxy measure for skill.

There are four observations that stand out from this figure. First, the wage distribution, conditional on experience is quite similar between public and not-for-profit (mostly Church-owned) providers, consistent with the idea that not-for-profits adopt wage tables used in the public sector. Second, we see that public and not-for-profit providers pay higher wages on average when compared

25See shorturl.at/zAB26, accessed September 7, 2021.
to for-profit nursing homes across all experience levels. Third, the wages in not-for-profits are compressed across experience levels (on average) when compared to for-profit nursing homes. At low experience levels, average wages differ by about 20%. In contrast, average wages are quite comparable at high experience levels of more than 15 years. Fourth, wages in not-for-profits are compressed conditional on experience levels. The interquartile range of wages is considerably smaller in not-for-profits when compared with for-profits. Both of these patterns are consistent with public wage schedules allowing the wage to vary by age (which is going to be imperfectly correlated with experience), while for-profits can reward more skilled workers more relative to lower-skilled, or less experienced, workers.

The right graph displays the distribution of employed workers by experience. For-profits disproportionately employ less experienced workers. For-profit firms pay lower wages and hence (all else equal\textsuperscript{26}) we would expect workers to prefer employment at public and not-for-profit providers. The ability of for-profits to sustain a substantial workforce at lower wages suggests that employment opportunities are rationed in public and not-for-profit nursing homes, particularly at the lower end of the skill distribution.

In sum, these facts imply that as the long-term care insurance was rolled out, the inpatient labor market was constrained by collective bargaining agreements. Especially at lower skill levels, most firms in the industry were paying above the market-wage, but rationing the number of vacancies. We next incorporate this friction into an equilibrium model of the long-term care labor market.

5.2 Model Setup

Environment: The production of the economy is populated with potential firms and workers. Workers differ in their skill level $\phi$ and for each skill level there is a continuum of workers in the economy. A worker of skill level $\phi$ can produce $\phi$ units of output if employed by a firm. As in Acemoglu and Shimer (1999), we assume that each firm has a production technology that requires one worker and there is a continuum of firms. Firms can open jobs in different industries and may

\textsuperscript{26}Anecdotal evidence suggests that, in addition to the wage differentials, workers may have intrinsic preference for working in a Church-owned or other not-for-profit providers. In combination with higher wages, the not-for-profit jobs, are thus generally more desirable.
be subject to different wage-setting frictions. Let $j \in J$ index labor markets—all firms in $j$ are operating in the same industry and face the same wage setting constraints. We assume there is a continuum of potential firms in each labor market $j$.

Workers and firms meet via search. Firms first decide whether to enter a market and which skill segment to enter in. Conditional on entry, each firm posts a vacancy with a wage $w_{j}^{\phi}$ (which will be common among all firms in $j$ in equilibrium). If $j$ is a market that is subject to binding wage-setting frictions, e.g. due to collective bargaining, firms set $w_{j}^{\phi}$ to equal the wage floor. In the next stage, workers observe all wage offers for their skill type and decide which labor market $j$ to search in. Each worker of skill $\phi$ then applies to one job in the labor market with wage $w_{j}^{\phi}$. Following Acemoglu and Shimer (1999), we denote the ratio of the number of applicants to the number of vacancies in each labor market $j$ and skill segment $\phi$ with $q_{j}^{\phi} > 0$ and refer to this as the expected queue length. The queue length measures the degree of competition in each labor market segment. Each applicant is hired with a probability $\mu(q_{j}^{\phi})$. If hired, the worker earns wage $w_{j}^{\phi}$. Otherwise the worker remains unemployed and obtains unemployment benefits or benefits form home production and leisure, which we allow to vary by skill level, $b^{\phi}$. For any worker, the probability of being hired is lower in markets that have a longer queue (i.e. $\mu(q_{j}^{\phi})$ is decreasing in $q_{j}^{\phi}$). Conversely, for any firm in market $j$, skill segment $\phi$, the probability of hiring a worker, denoted with $\eta(q_{j}^{\phi}) = \mu(q_{j}^{\phi}) \times q_{j}^{\phi}$, is increasing in $q_{j}^{\phi}$. In other words, firms have higher chances of filling vacancies in labor markets that have more applicants for any fixed number of open positions.

**Payoffs:** There are three types of agents in the economy—firms, workers, and consumers of the final good. We describe each of their payoffs in turn. A firm’s payoff is its profit. For a firm in market $j$ that has entered skill segment $\phi$, the profit in this skill segment is given by:

$$\pi_{j}^{\phi} = \eta(q_{j}^{\phi}) \times (p_{j} \times \phi - w_{j}^{\phi}) - c \times \phi.$$  

Here, $c \times \phi$ denotes the cost of vacancy posting, capturing recruiting and retention costs. We assume that these are proportional to worker skill (it is costlier to hire higher-skilled workers) and are incurred with certainty—irrespective of whether the firm manages to fill the vacancy. With
probability \( \eta(q_j^\phi) \), the firm fills its vacancy, produces output, collects revenue, and pays wages. This is captured by the first term of the profit function. Matched workers earn wage \( w_j^\phi \) (which is equal to wage floor for constrained firms) and produce \( \phi \) units of output valued at \( p_j \) each.

Worker \( i \)'s payoff is the expected utility from directing their search toward labor market \( j \). The expected utility is given by expected earnings:

\[
u_{ij} = \mu(q_j^\phi(i)) \times w_j^\phi(i) + (1 - \mu(q_j^\phi(i))) \times b^{\phi(i)} + \epsilon_{ij}.
\] (5)

\( \epsilon_{ij} \) denotes an idiosyncratic preference shock that worker \( i \) may have for labor market \( j \). For example, prior experience or preference in industry or living closer to market \( j \) may lead the worker to prefer that labor market, all else equal.

Finally, we consider a representative consumer who has preferences over output produced in the sectors of the economy and a numeraire good. The consumer solves

\[
\max_X v(X) - \sum_j p_j^c \times X_j
\] (6)

where \( v(X) \) is EUR-denominated utility from consuming the vector of output quantities \( X \) and \( \sum_j p_j^c \times X_j \) denotes expenditures (utility from and spending on the numeraire good cancel out.) We allow \( p_j \) paid by consumers (which we denote with \( p_j^c \)) to differ from the \( p_j \) collected by firms. This difference can arise if the government offers subsidies for a subset of goods. We introduce a fixed unit subsidy (per unit of output) for one specific industry that may encompass multiple labor markets—in our empirical application that industry is long-term care. Let \( \tau_g \) denote the subsidy amount that is offered in industry \( g \) of the economy; we assume that the subsidy does not vary across markets or firms within the industry. Then, \( p_j^c = p_j - \tau_{g(j)} \), with \( \tau_{g(j)} = 0 \) for non-subsidized industries (if \( j \notin g \)).

**Equilibrium:** We define the search equilibrium as a tuple of wages, queue lengths, output prices, and output quantities with the following properties. First, workers apply to the job that maximizes expected utility. The share of workers who apply to jobs in labor market \( j \) is given in equation
Second, output markets clear in each labor market and product demand $X_{j}^{D}(p_{c})$ equals supply $X_{j}^{S}(p)$, see equation (10). Third, firms maximize profits, taking output prices as given, subject to institutional wage-setting constraints if any (in our empirical setting, not-for profits firms in long-term care are subject to collective bargaining, while private firms are not), see equation (11). Under free entry, firms profits are equated to zero, see equation (8).

Building on proposition 1 in Acemoglu and Shimer (1999), the equilibrium solves the following optimization problem:

$$\begin{align*}
\max_{w^{\phi}, q^{\phi}} & \quad u_{ij} \\
\text{s.t.} & \quad \eta(\phi_{j}) \times (p_{j} \times \phi - w_{j}^{\phi}) - c \times \phi = 0 \\
& \quad s_{j}^{\phi}(w^{\phi}, q^{\phi}) = Pr[u_{ij} \geq u_{ik}, k \neq j] \\
& \quad X_{j}^{D}(p_{c}) = X_{j}^{S}(p) = \sum_{\phi} s_{j}^{\phi}(w^{\phi}, q^{\phi}) \times \mu(q_{j}^{\phi}) \times \phi \\
& \quad w_{j}^{\phi} = \Delta w + \beta \times (p_{j} \times \phi) \quad \text{if} \ j \text{ is constrained by collective bargaining.}
\end{align*}$$

In words, in equilibrium, firms choose the set of wages and queue lengths for each skill level that maximize worker flow utilities subject to the constraints discussed above. That means that in all markets that are not subject to collective bargaining, constrained firms post efficient wages (constrained by search frictions) that depend on the elasticity of the matching function (Moen, 1997; Acemoglu and Shimer, 1999). Wages in markets constrained by collective bargaining are determined exogenously. Higher wages are accompanied by longer queues in equilibrium. This implies that labor markets with a binding collective bargaining agreement will be more competitive for workers when regulated wages exceed the competitive wage. Competing firms that post unconstrained competitive wages for the same type of jobs will find it more difficult to match with workers (lower $\eta$) such that a cost advantage from lower wages is implicitly offset by higher recruiting and retention costs. See Appendix D for derivations of equilibrium wages and queues.
5.3 Product Subsidies and Welfare

5.3.1 Welfare function

We define social welfare as the sum of consumer surplus, producer surplus, worker surplus, net of
government spending.\(^\text{27}\) To simplify the exposition, we assume that the idiosyncratic preference
shocks in the worker’s utility function are i.i.d. extreme value, which gives us a closed-form expres-
sion for the worker’s surplus and the probability \(s_j^\phi\) that a worker of skill \(\phi\) applies for a job \(j\). We
then have:

\[
\begin{align*}
W &= v(X) - \sum_j p_j^X \times X_j + \sum_j \sum_\phi s_j^\phi (w^\phi, q^\phi) \times \left[ \mu(q_j^\phi) \times (p_j \times \phi - w_j^\phi) - \frac{c \times \phi}{q_j^\phi} \right] \\
&\quad + \sum_\phi \left[ \log(\sum_j \exp(\mu(q_j^\phi) \times w_j^\phi + (1 - \mu(q_j^\phi)) \times b^\phi)) \right] \\
&\quad - \sum_j \sum_\phi s_j^\phi (w^\phi, q^\phi) \times \left[ \mu(q_j^\phi) \times \phi \times \tau(q(j)) + (1 - \mu(q_j^\phi)) \times UEB \right],
\end{align*}
\]

where \(UEB\) denotes unemployment benefits. In short, consumer surplus follows directly from
equation (6) and is evaluated at equilibrium prices and quantities. Firm profits depend on successful
matches, given by the share of applicants times their conditional match rate \((s_j^\phi \times \mu_j^\phi)\) times , and
the total cost of job posting, given by the share of applicants \((s_j^\phi)\) times the costs per applicant
\(\frac{c \times \phi}{q_j^\phi}\). Worker surplus is the expected utility from directed search \((E[\max_j u_{ij}])\) which equals the
displayed inclusive value when preference shocks are i.i.d. extreme value. Finally, government
spending amounts to either a subsidy spending if a worker is hired, or an unemployment benefit
payment if a worker is not hired.

\(^{27}\)This formulation abstracts away from the costs of raising public funds, which can of course be added.
5.3.2 Product Subsidy

Next, we turn to the effect of introducing a product-market subsidy on social welfare. As we show in Appendix D, the effect of a product-market subsidy in an industry operates through two key mechanisms: (1) changes in job applications \( s_j^\phi(w^\phi, q^\phi) \) that capture the reallocation between labor markets, and (2) changes in labor market queues \( q_j^\phi \) that capture the reallocations within labor markets. Formally, this amounts to:

\[
\Delta W = \int_0^{\bar{\tau}_g} \frac{\partial W}{\partial \tau_g} \, d\tau_g = \int_0^{\bar{\tau}_g} \sum_j \sum_\phi \left( \frac{\partial W}{\partial s_j^\phi} \times \frac{\partial s_j^\phi}{\partial \tau_g} + \frac{\partial W}{\partial q_j^\phi} \times \frac{\partial q_j^\phi}{\partial \tau_g} \right) \, d\tau_g
\]

\[
= \int_0^{\bar{\tau}_g} \sum_j \sum_\phi \left( -\tau_g(j) \times \phi \times \left( \frac{\partial m_j^\phi}{\partial s_j^\phi} \times \frac{\partial s_j^\phi}{\partial \tau_g} + \frac{\partial m_j^\phi}{\partial q_j^\phi} \times \frac{\partial q_j^\phi}{\partial \tau_g} \right) UEB \right)
\]

\[
- \left( \frac{\partial \omega_j^\phi}{\partial s_j^\phi} \times \frac{\partial s_j^\phi}{\partial \tau_g} + \frac{\partial \omega_j^\phi}{\partial q_j^\phi} \times \frac{\partial q_j^\phi}{\partial \tau_g} \right) \times \left( \frac{\partial m_j^\phi}{\partial \mu} \times \frac{\partial q_j^\phi}{\partial \tau_g} \right)
\]

\[
+ \left( \frac{\partial m_j^\phi}{\partial \mu} \times \frac{\partial q_j^\phi}{\partial \tau_g} \right) \times \left( \frac{w_j^\phi - (\epsilon \times p_j \times \phi + (1 - \epsilon) \times b^\phi)}{1 - \epsilon} \right) \right) \, d\tau_g \quad (13)
\]

where \( m_j^\phi = \mu(q_j^\phi) \times s_j^\phi(w^\phi, q^\phi) \)—the population share of workers of skill \( \phi \) employed in (matched to) firm \( j \), and \( \omega_j^\phi = (1 - \mu(q_j^\phi)) \times s_j^\phi(w^\phi, q^\phi) \)—the (population) share of workers who applied to \( j \) but were not matched and remained unemployed, and \( \epsilon = \frac{\eta'(q_j^\phi) \times q_j^\phi}{\eta(q_j^\phi)} \) is the elasticity of the matching function. We integrate over the full subsidy path from \( \tau_g = 0 \) to \( \tau_g = \bar{\tau}_g \) (recall that \( \tau_j = 0 \) for all unsubsidized industries) and sum changes across all firms and worker skill levels. The overall welfare effect can be decomposed into three sets of effects: traditional deadweight loss from subsidies (or moral hazard), fiscal externalises, and labor market surplus.

The traditional deadweight loss in the product market is proportional to the overall change in employment stemming from relocation between industries \( (\partial m_j^\phi / \partial s_j^\phi) \) but also the relocation within industries \( (\partial m_j^\phi / \partial q_j^\phi) \). Consistent with Harberger (1971), the formula allows for distortions

---

28Changes in wage and output price, conditional on \( s_j^\phi(w^\phi, q^\phi) \) and \( q^\phi \), are transfers between stakeholders and do not add to welfare see Appendix D.
in the product markets in the outside industries $\tau_0 \neq 0$, which have a first order effect on welfare. The second term captures fiscal externalities, which are proportional to the overall change in non-employment (stemming again from both relocation channels). The third term captures the welfare effect in the labor market which is proportional to the wedge between the “efficient” wage (constrained only by search frictions), $\epsilon \times (p_j \times \phi) + (1 - \epsilon) \times b^\phi$, and the equilibrium wage, $w^\phi_j$. Firms in labor markets that are not affected by collective bargaining will post the efficient wage, setting the wedge to zero. In contrast, when collective bargaining frictions lift equilibrium wage beyond the efficient wage, unemployment will be inefficiently high. In this case, decreases in the labor market queue length contribute positively to social welfare. The opposite holds true when the equilibrium wage falls below the efficient wage level.\footnote{In contrast to the first two terms, the labor market term only scales in within industry changes in unemployment. Labor market surplus increases when workers who already search for work in a given sector are more likely to find employment, provided that labor market tightness was inefficiently low to begin with.\footnote{For comparison, in a random search model with Nash bargaining over wages, the wedge in wages boils down to whether the Hosios (1990) condition holds, which requires that the Nash bargaining weight equals the elasticity of the matching function.}}

In contrast to the first two terms, the labor market term only scales in within industry changes in unemployment. Labor market surplus increases when workers who already search for work in a given sector are more likely to find employment, provided that labor market tightness was inefficiently low to begin with.\footnote{For comparison, in a random search model with Nash bargaining over wages, the wedge in wages boils down to whether the Hosios (1990) condition holds, which requires that the Nash bargaining weight equals the elasticity of the matching function.} The relocation of employment between labor markets does not contribute directly to the labor market surplus as the marginal worker is indifferent between labor markets. Whether such relocation is welfare enhancing is ambiguous in our framework. On one hand, employment gains in the subsidized industry enter negatively through the traditional deadweight loss channel (Baicker and Chandra, 2012b). On the other hand, overall unemployment in the economy may fall when workers relocate towards labor markets with lower unemployment rates, generating positive fiscal externalities. The sign of the net effect is thus an empirical question in any given setting.

**Graphical Discussion:** To develop a better intuition for the three channels outlined in equation (13) we provide a graphical illustration. To simplify the exposition, we focus on one labor market only and abstract form worker skill heterogeneity by considering the case of $\phi = 1$. We also consider a “frictionless” matching process, where the shorter side of the market is fully employed.\footnote{Our framework allows for wage distortions in other labor markets that may also be affected by collective bargaining frictions. For instance, if the SNF subsidy reduces demand for output from the outside sector then prices and hence labor market tightness will fall in the outside sector. This would add negatively to social welfare if labor market tightness was inefficiently low in the outside sector.}
Specifically, we assume that vacancies are the shorter side of the market, meaning that every vacancy is filled with probability $\eta = 1$. This implies a matching elasticity of $\epsilon = 0$. In this case, the efficient equilibrium wage simplifies to $w^\phi = b^\phi$ and the wage wedge corresponds to the difference between the going wage and the value of unemployment benefits, home production, and leisure.

Figure 5 presents the demand and supply of output (equal to employment for $\phi = 1$). The vertical axis denotes the willingness-to-pay (WTP) for output and the firm’s marginal cost (MC) of production in EUR. The horizontal axis denotes output. The solid downward-sloping line denotes the demand for output absent a subsidy (captured by the marginal utility, see equation (6)). $MC^{CB}$ denotes the marginal cost of production under collective bargaining frictions, which is the sum of the exogenously determined wage $W$ and the costs per vacancy $c$. The equilibrium is denoted by point $A$ and output amount $X$ is produced. Introducing a unit subsidy shifts out the demand curve by the subsidy amount $\tau$. Output increases to $X'$ and $A'$ denotes the new equilibrium.

How does welfare change in this market? First, the subsidy leads to a deadweight loss in the product market from (traditional) moral hazard, denoted by the triangle $AA'C$. This effect corresponds to the first line in equation (13). Second, the efficient wage (arising in the competitive search equilibrium) equals $b$ when $\epsilon = 0$, which is smaller than the going wage $W$ in this case. This can be seen by the difference between $MC^{CB}$ and the private marginal costs absent collective bargaining friction, $MC^{*P}$. That means that because of wage compression under collective bargaining some gains from trade between private parties were left on the table. The subsidy brings output quantity closer to the private optimum $A^{*P}$, generating a welfare gain in the labor market. The effect size is denoted by the rectangle $AA'BB'$ and corresponds to the third line in equation (13). Finally, we consider the fiscal externalities. Absent alternative labor markets, we assume that increases in output result in a reduction in unemployment generating a positive externality worth the unemployment benefit $UEB$. Internalizing this externality, the marginal social cost falls by $UEB$ from $MC^{*P}$ to $MC^{*S}$. That means that the subsidy generates a positive fiscal externality denoted by the rectangle $BB'DD'$, which corresponds to the second line in equation (13).

In this example the welfare gains outweigh the traditional deadweight loss from (traditional) moral hazard as evidenced by a positive net welfare effect of size $ACD'D$. 

31
5.4 Welfare Effects of LTC Insurance Expansion

We now provide a back-of-the-envelope quantification of the theoretical object in Equation 13 in our empirical setting. To make the computation tractable, we impose two simplifying assumptions. First, and following the graphical discussion, we consider a frictionless matching process in which vacancies are the shorter side of the market, which implies a matching elasticity of $\epsilon = 0$. This assumption provides a lower bound on welfare effects in the labor market and is consistent with the absence of significant increases in wages in the data. This assumption also helps us approximate the magnitude of the traditional deadweight loss from moral hazard as we explain below. Second, we assume that SNFs produce homogeneous products such that the output price is equalized across wage-constrained (not-for-profit) and wage unconstrained (private for-profit) SNF labor markets.

**Traditional DWL:** Assuming a linear relationship between SNF employment and the subsidy allows us to approximate the traditional deadweight loss through the Harberger triangle.\(^{31}\)

\[
\text{Traditional DWL} \approx -\frac{1}{2} \times \bar{\tau}_{SNF} \times \sum_{j \in SNF} \sum_{\phi} \phi \times \Delta Employment_{j}^{\phi}
\]

\[
= -\frac{1}{2} \times \bar{\tau}_{SNF} \times \frac{p_{SNF}}{p_{SNF}} \times \sum_{j \in SNF} \sum_{\phi} \phi \times p_{SNF} \times \Delta Employment_{j}^{\phi}
\]

\[
\approx -\frac{1}{2} \times 57\% \times \sum_{j \in SNF} \sum_{\phi} \left(1 + \frac{c \times \phi}{w_{j}^{\phi}}\right) \times w_{j}^{\phi} \times \Delta Employment_{j}^{\phi}
\]

\[
\approx -\frac{1}{2} \times 57\% \times (1 + 15\%) \times 30,000 \text{ EUR} \times 37,600 = -370 \text{ million EUR}
\]

The first estimate we need is that of the cost-sharing level. Around the period of LTC insurance expansion (in 1999), market prices for SNF patients equaled around 65 EUR per patient per day for healthcare services and another 18 EUR per patient per day for room and board.\(^{32}\) LTC insurance offered patients with these needs financial support of 2,800 Deutsche Mark per month, which corresponds to roughly 1,400 EUR per month, or 1,400 / 30 = 47 EUR per day. This

---

\(^{31}\)When $m(\tau) = a + b \times \tau$, we have that $\int_{\tau}^{\bar{\tau}} \tau \times \frac{\partial m}{\partial \tau} d\tau = \frac{1}{2} \times \bar{\tau} \times \Delta m$, where $\Delta m = b \times \bar{\tau}$.

\(^{32}\)See Durchschnittliche Vergütung fuer vollstationaere Dauerpflege in Pflegeheimen (pro Person und Tag in Euro). Gliederungsmerkmale: Jahre, Region, Pegelklasse/Unterkunft und Verpegung, reported by Gesundheitberichterstattung des Bundes - Gemeinsam getragen von RKI und DESTATIS.
implies that the subsidy covered \( \frac{\text{p}_{\text{SNF}}}{\phi_{\text{SNF}}} \approx \frac{47\text{EUR}}{65\text{EUR}+18\text{EUR}} = 57\% \) of the price.\(^{33}\) We next turn to the estimate of hiring costs. Following Boeri and Burda (2009), we assume that hiring costs equal 15% of wage costs: \( \frac{c \times \phi}{w_j} \approx 15\% \). Next, from the free entry condition we know that when \( \eta = 1 \), \( \phi \times p_g = w_j^\phi + c \times \phi \). We then replace \( w_j^\phi \) by the average annual income of new SNF hires (30,000 EUR) and multiply by the number of new jobs that were created in SNFs (37,600) to arrive at an estimate of the traditional deadweight loss of 370 million EUR.

**Fiscal Externalities:** We approximate the fiscal externalities by the overall change in unemployment multiplied by the average unemployment benefit:

\[
\text{Fiscal Externalities} \approx -\text{UEB} \times \sum_j \sum_{\phi} \Delta \text{Unemployment}_j^\phi \\
\approx 12,000 \times \sum_{j \in \text{SNF}} \sum_{\phi} \Delta \text{Employment}_j^\phi \\
\approx = 12,000 \text{ EUR} \times 37,600 = 451 \text{ million EUR}
\]

We estimate the average unemployment benefits in our “at risk” sample to be equal 33 EUR per calendar day or 12,000 EUR per year. Building on our estimates, we assume that all newly hired workers would otherwise have been receiving unemployment benefits, arriving at a positive fiscal externality of 451 million EUR.

**Labor Market Surplus:** Lastly, we approximate the labor market welfare effects as a product of changes in employment and wage wedges:

\(^{34}\)In our conceptual framework the subsidy is paid per unit of worker output. The actual subsidy was paid per patient month. To reconcile the two, we interpret \( \phi \) as the number of patient days that can be cared for by each worker of type \( \phi \). That allows us to interpret the output price \( p_{\text{SNF}} \) as the price per patient day.
Labor Market Surplus \approx \sum_{j \in SNF,j \neq FP} \sum_{\phi} (w_{j}^{\phi} - w_{j}^{*}) \times \Delta Employment_{j}^{\phi} \\
= \sum_{j \in SNF,j \neq FP} \sum_{\phi} (w_{j}^{\phi} - w_{SNF,FP}^{\phi}) \times \Delta Employment_{j}^{\phi} \\
\approx 20\% \times 30,000EUR \times 75\% \times 37,600 = 169\text{millionEUR}

For-profit SNFs are not constrained by collective bargaining and we can thus use their wages as a measure of the efficient wage in the market. This also implies that their employment changes do not contribute to changes in the labor market surplus. We therefore only consider employment changes in the public and not-for-profit SNF labor markets, denoted by \( \sum_{j \in SNF,j \neq FP} \). Absent employment changes in non-SNF sectors of the economy (as we find empirically), we assume that the employment gains in SNF labor markets are entirely stemming from a relocation within (as opposed to between) labor markets. We can then estimate the relevant change in employment as 75\% (share not-for-profit and public SNFs) of the total SNF employment gains. Turning to the wage wedges, we note that (by assuming homogenous products) output prices are equalized between different SNF ownership types. That means that wages posted in the for-profit SNF labor markets are the same as the efficient wage in all SNF labor markets. This, in turn, implies that we can use the difference between observed wage levels in for-profit and public/not-for-profit SNFs as an estimate of wage wedges, which amounts to 20\% of average salary of 30,000 EUR.

This measurement approach abstracts away from nonpay job characteristics that may contribute to wage differentials (Sorkin, 2018). Specifically, the welfare gains in the labor market would be smaller (and potentially negative) when wage differences partially (or fully) reflect compensating differentials. In contrast, and as emphasized by Mortensen (2003), higher-paying jobs may also have more desirable nonpay characteristics when worker utilities are not equalized across jobs as in our setting. While estimating non-wage job attributes is beyond the scope of this paper, anecdotal evidence suggests that not-for-profit SNFs provide more attractive work environments augmenting the difference to for-profit wages. This suggests that our approach likely understates the wedges in the labor market. Multiplying employment gains in not-for-profit and public SNFs with
our estimate of wage wedges gives us a labor market surplus estimate of 169 million EUR.

The measurement of the wage wedge assumes a constant elasticity of the matching function in SNF labor markets within a skill segment. Popular and more flexible matching functions have that the matching elasticity is actually falling in the queue length. This would suggest that the efficient wage for not-for-profit SNFs is again smaller than the wage paid in for-profit SNFs and that our approach likely understates the wedges in the labor market.\textsuperscript{34}

\textbf{Discussion} Our estimates suggest that welfare gains from internalizing fiscal externalities and wage distortions arising from collective bargaining may offset the traditional deadweight loss from moral hazard and that a product-market subsidy can be welfare enhancing on net in the second best sense. These offsetting effects are particularly large in our empirical setting as the employment gains are entirely driven by formerly unemployed workers. Interpreted through the lense of a labor market model with frictions, this suggests that queues for SNF jobs were relatively long, consistent with collective bargaining wage floors and a high unemployment rate at the time, and that idiosyncratic preference shocks $\epsilon_{ij}$ were sufficiently large such that workers were not willing to switch across labor markets following an increase in SNF vacancy postings.

We would expect the fiscal externalities and the gains in the labor market surplus to be sufficiently smaller in economic environments with shorter queues in the labor market that produces the subsidized good (Baicker and Chandra, 2012a). If workers define the shorter market side, employment expansion will largely involve the relocation workers across labor markets, muting the potential gains in the labor market. The wage wedge may even turn negative in the expanding labor market, resulting in a potentially negative net effect on labor market surplus. The fiscal externalities would then also be significantly smaller since a share of new SNF workers would already come from employment in the outside sector rather than unemployment, particularly so when demand for the outside good is high (Stevens et al., 2015).

\textsuperscript{34}An alternative matching function, discussed in Acemoglu and Shimer (1999), implies $\eta(q) = 1 - \exp(-q)$. The elasticity is then $\epsilon(q) = \frac{q \times \exp(-q)}{1 - \exp(-q)}$, which is weakly decreasing in $q$ for $q \geq 0$, see the Appendix for details. The shorter queue length in for-profit SNFs then suggests a higher elasticity and that the for-profit equilibrium wage, $\epsilon(q) \times p \times \phi + (1 - \epsilon(q)) \times b'$, weakly exceeds the efficient wage for not-for-profit SNFs if $p \times \phi \geq b'$, which is a necessary condition for employment.
6 Conclusion

Arrow (1963) hypothesized that demand-side moral hazard induced by health insurance can lead to supply-side expansions in health-care markets. Capturing this general equilibrium conjecture empirically has been challenging. In this paper, we combine detailed administrative labor market data with a rarely observed rollout of a universal insurance program—the introduction of national long-term care (LTC) insurance in Germany in 1995—to shed new light on how insurance expansions can affect the allocation of health-care professionals across sectors.

We start by documenting a dramatic expansion of the LTC labor market. A 10 percentage point expansion in the share of insured elderly leads to 0.05 (7%) more inpatient LTC firms and four (13%) more workers per 1,000 elderly in Germany. Wages did not increase on average, while the quality of newly hired workers declined. We find suggestive evidence of a reduction in old-age mortality.

The second part of our analysis then considers workers who are marginal to SNF employment. Analyzing these workers’ counterfactual employment decisions allows us to assess potential employment spillover effects to other sectors of the economy and welfare. We find no evidence for negative spillover effects on employment in other sectors of the economy. Instead, we find a substantial reduction in unemployment that can fully account for our estimated increase in SNF employment. This suggests that, in this particular empirical setting, the marginal SNF hires would have collected unemployment benefits in the absence of insurance expansion.

To reconcile these findings, the last part of our analysis discusses a conceptual framework that allows for the existence of labor market frictions and unemployment on the supply side of care. Specifically, we emphasize the important role of collective bargaining and wage compression in SNF markets, which may introduce a wage floor for lower-skilled workers. Consistent with this observation, we estimate a reservation wage of only 64% of the going wage. This difference points to large gains in worker surplus and can explain why inpatient LTC providers hired predominantly lower-skilled workers without raising wages. Second, we incorporate the distortionary effects of unemployment benefits that equal about 39% of the going wage. Netting these out, the social cost of employment is only 64 – 39 = 25% of the going wage among new hires. Combining these estimates,
we calculate that LTC insurance expansion increased labor market welfare by 576 million EUR per year among new hires, likely exceeding the traditional deadweight loss in the product market.

Together, our findings suggest that the LTC insurance expansion has generated substantial surplus in the labor market, by lifting lower-skilled workers out of unemployment and by mitigating the distortionary effects of wage compression and unemployment benefits.
References


Grant, Iris, Iris Kesternich, and Johannes Van Biesebroeck, “Entry Decisions and Asymmetric Competition between Non-Profit and For-Profit Homes in the Long-Term Care Market,” *KU Leuven, Faculty of Economics and Business (FEB), Department of Economics, Leuven*, 2019.


Human Mortality Database. University of California Berkeley (USA), and Max Planck Institute for Demographic Research (Germany). Data available at [www.mortality.org](http://www.mortality.org) or [www.humanmortality.de](http://www.humanmortality.de) (data downloaded in September 2021).


Notes: Panel A displays the evolution of the total public spending on long-term care benefits in Germany from 1990 to 2008, and separately by means-tested benefits (Hilfe zur Pflege) and universal long-term care insurance. Universal LTC insurance started covering outpatient services in 1995 and inpatient services in 1996. These transition years are shaded in grey. Panel B displays the counts of regular (see Appendix B.2 for definition) employees in inpatient long-term care (SNF) over time. Panel C shows the counts of regular SNF employees per 1,000 individuals age 65 and over. Panel D shows the number of individuals age 65 and over time. Data underlying panels B and C have been restricted to West Germany excluding Bremen and Berlin, panel D is all of West Germany. Data source for panel B is Pflegestatistik 1999, available at www.statistischebibliothek.de; for panels B and C the analytic files constructed from the universe of Integrated Employment Biography data (Appendix B.1); for panel D - Human Mortality Database.

LTC=Long-Term Care; SNF=Skilled Nursing Facility (inpatient LTC).
Figure 2: Introduction of Universal LTC Insurance and Supply of SNF Care

(A) SNF Firms per 1,000 65+ Population

(B) SNF Workers per 1,000 65+ Population

(C) SNF Firms, Event Study

(D) SNF Workers, Event Study

Notes: The top panels plot the average—across counties—number of SNF firms (panel A) and of SNF workers (panel B) per 1,000 individuals age 65+ and over, in 1975-2008. The county-level average is computed separately for the group of West German counties with (region-level) exposure variable $E_r$ above and below the median across counties. All counties at the median are assigned to the below median group. Both time-series are normalized to the aggregate mean across all counties in 1993. Panels C and D display $\lambda_t$ coefficients and 95% confidence intervals from estimating the specification in Equation 2 with the number of SNF firms (panel C) or workers (panel D) as an outcome. Coefficients $\lambda_t$ were normalized to zero in the pre-reform year $t=1993$. $\lambda_t$ multiply the exposure variable $E_r$ that takes values from 0 to 1 and measures the share of potential long-term care patients who did not have public assistance for LTC prior to the rollout of universal LTC insurance (mean of $E_r=0.686$). The geographic variation in $E_r$ is visualized in Figure A.1. The mean of outcome variables in 1993 is reported in Table 2.
Notes: Panel A displays the raw time series of average mortality rates in the age 75+ population, bifurcated into counties above and below median exposure to the LTC insurance expansion $E_r$. Panel B displays the time series of average mortality rates in the age 75+ population in the entirety of West Germany (including Bremen and Berlin) combined with a counterfactual time series of mortality. The counterfactual time series is constructed using the synthetic control method following Abadie et al. (2010). The treatment year in the synthetic control model is defined to be 1995. Corresponding event study estimates are reported in Table 5. Data source for panel A are statistical agencies of the West German federal states, excluding Bremen and Berlin. The data source for panel B is the Human Mortality Database.
Figure 4: Wages and Employment by Experience and Ownership: Nursing Assistants

Notes: Panel A displays average daily wages observed among workers with occupational code for nursing assistants during their SNF employment spells. The sample is split by SNF ownership type and the number of years of health care experience of each worker (counting any spells in firms with healthcare-related industry classification codes and not only SNF employment). Panel B displays, for the same occupation of nursing assistants, the distribution of employees by their overall experience in firms with healthcare-related industry classifications.
Figure 5: Labor Market Equilibrium under Wage Frictions

\[ MC^{CB} = W + c \]
\[ MC^{\ast,p} = b + c \]
\[ MC^{\ast,S} = MC^{\ast,p} - UI \]
### Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>SNF Sample</th>
<th>Labor Market Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Spells</td>
<td>SNF Spells</td>
</tr>
<tr>
<td></td>
<td>1975-08</td>
<td>1975-08</td>
</tr>
<tr>
<td>No. of Individual-Year Observations</td>
<td>24,369,708</td>
<td>9,834,229</td>
</tr>
</tbody>
</table>

#### Individuals

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Unique Individuals</td>
<td>1,589,014</td>
<td>1,589,014</td>
<td>3,818,780</td>
</tr>
<tr>
<td>Demographics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Age</td>
<td>37.7</td>
<td>41.0</td>
<td>41.1</td>
</tr>
<tr>
<td>% Female</td>
<td>77.3</td>
<td>80.6</td>
<td>41.3</td>
</tr>
<tr>
<td>% German</td>
<td>94.1</td>
<td>93.8</td>
<td>92.0</td>
</tr>
<tr>
<td>% High School Education (Abitur)</td>
<td>10.0</td>
<td>9.3</td>
<td>10.5</td>
</tr>
<tr>
<td>% in Healthcare Sector</td>
<td>61.0</td>
<td>100.0</td>
<td>6.3</td>
</tr>
<tr>
<td>% Unemployed</td>
<td>9.6</td>
<td>0.0</td>
<td>6.7</td>
</tr>
<tr>
<td>Mean 15-Year Labor Market Experience (yrs)</td>
<td>8.4</td>
<td>8.8</td>
<td>10.2</td>
</tr>
<tr>
<td>Mean 15-Year SNF Experience (yrs)</td>
<td>3.6</td>
<td>6.0</td>
<td>0.0</td>
</tr>
<tr>
<td>% Part-Time&lt;sup&gt;b&lt;/sup&gt;</td>
<td>27.3</td>
<td>32.7</td>
<td>13.0</td>
</tr>
<tr>
<td>Mean Daily Wage (EUR)&lt;sup&gt;c&lt;/sup&gt;</td>
<td>77.5</td>
<td>82.9</td>
<td>105.4</td>
</tr>
<tr>
<td>All Observations</td>
<td>82.9</td>
<td>82.9</td>
<td>80.1</td>
</tr>
</tbody>
</table>

#### Establishments

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Unique Establishments</td>
<td>953,497</td>
<td>18,675</td>
<td>1,532,794</td>
</tr>
<tr>
<td>Any</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SNF</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Of SNF Employment Spells, % in</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% For-Profit SNF</td>
<td>26.9</td>
<td>29.8</td>
<td></td>
</tr>
<tr>
<td>% Church-Owned SNF</td>
<td>58.9</td>
<td>56.2</td>
<td></td>
</tr>
<tr>
<td>% Publicly-Owned SNF</td>
<td>14.2</td>
<td>13.9</td>
<td></td>
</tr>
</tbody>
</table>

<sup>a</sup> SNF=Skilled Nursing Facility (inpatient long-term care)

<sup>b</sup> Conditional on being employed.

<sup>c</sup> In constant 2020 Euros.

**Notes:** The table reports a selection of summary statistics for the two main analytic samples “SNF Sample” and “Labor Market Sample.” Both are extracts from the universe of the German Integrated Employment Biographies data for years 1975-2008. “SNF Sample” is the annualized (taking the spell observed on June 30th of a given year) set of full labor market biographies for individuals who had at least one regular employment spell in a SNF over the course of 1975 to 2008. “Labor Market Sample” is a 10% draw from the annualized universe of labor market biographies, restricted to individuals over 25 who did not have a history of SNF employment five years before each index year. See Section 2 and Data Appendix B.1 for details.
Table 2: Event Study Results: Aggregate Response

<table>
<thead>
<tr>
<th></th>
<th>Firms (1)</th>
<th>Workers (2)</th>
<th>Full-time (3)</th>
<th>Part-time (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_{97-08}$</td>
<td>0.50</td>
<td>44.37</td>
<td>21.89</td>
<td>22.48</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(8.41)</td>
<td>(4.95)</td>
<td>(4.92)</td>
</tr>
<tr>
<td>Event Study Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Year Effect, $\lambda_{1997}$</td>
<td>0.32</td>
<td>25.58</td>
<td>13.36</td>
<td>12.23</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(6.93)</td>
<td>(4.34)</td>
<td>(3.29)</td>
</tr>
<tr>
<td>3-Year Effect, $\lambda_{1999}$</td>
<td>0.35</td>
<td>34.37</td>
<td>19.59</td>
<td>14.78</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(8.14)</td>
<td>(4.91)</td>
<td>(4.18)</td>
</tr>
<tr>
<td>5-Year Effect, $\lambda_{2001}$</td>
<td>0.37</td>
<td>43.10</td>
<td>24.98</td>
<td>18.12</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(8.92)</td>
<td>(5.44)</td>
<td>(4.82)</td>
</tr>
<tr>
<td>10-Year Effect, $\lambda_{2006}$</td>
<td>0.70</td>
<td>52.28</td>
<td>21.70</td>
<td>30.58</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(9.50)</td>
<td>(5.64)</td>
<td>(6.20)</td>
</tr>
</tbody>
</table>

Implied Impact

- Using In-sample Variation$^a$: 0.05, 4.03, 1.99, 2.04
- Aggregate Impact, West Germany$^b$: 443.20, 39,058, 19,268, 19,815

- Using Out-of-sample Variation$^c$: 0.34, 30.45, 15.02, 15.43
- Aggregate Impact, West Germany$^b$: 3,308, 295,192, 145,627, 149,565

Level of Outcome in 1993

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Observations</td>
<td>10,635</td>
<td>10,948</td>
</tr>
</tbody>
</table>

$^a$ Multiplies $\delta_{97-08}$ by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure.

$^b$ Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.

$^c$ Multiplies $\delta_{97-08}$ by the mean of the exposure variable across counties, $E_r = 0.686$.

Notes: The top panel displays the pooled coefficient $\delta_{97-08}$, obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using $E_r$, derived in Equation 1, as the measure of a county’s exposure to the reform. Outcome variables include the number of SNF firms and the number of regular SNF workers, in total (column 2) and separately by part-time and full-time status (columns 3 and 4) per 1,000 individuals age 65 and older. See Appendix B.2 for the definition of a SNF and a “regular” worker in SNF. The second panel displays $\lambda_t$ coefficients of the event study in Equation 2. Coefficients were normalized to zero in year $t = 1993$. The results are visualized in Figure 2. All specifications include county and year fixed effects. Standard errors clustered at the county-level are reported in parentheses.
Table 3: Event Study Results: SNF Wages

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Log Daily Full-Time SNF Wage</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>New Hires&lt;sup&gt;a&lt;/sup&gt;</td>
<td>(1)</td>
<td>(2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Incumbents&lt;sup&gt;b&lt;/sup&gt;</td>
<td>(3)</td>
<td>(4)</td>
<td></td>
</tr>
<tr>
<td><strong>Pooled Coefficients</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_{97-08}$</td>
<td>-0.08</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.01)</td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Event Study Results</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Year Effect, $\lambda_{1997}$</td>
<td>-0.05</td>
<td>-0.04</td>
<td>-0.00</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>3-Year Effect, $\lambda_{1999}$</td>
<td>-0.06</td>
<td>-0.01</td>
<td>-0.02</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.01)</td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>5-Year Effect, $\lambda_{2001}$</td>
<td>-0.09</td>
<td>-0.03</td>
<td>-0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.01)</td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>8-Year Effect, $\lambda_{2004}$</td>
<td>-0.18</td>
<td>-0.02</td>
<td>-0.03</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.05)</td>
</tr>
<tr>
<td><strong>Controls&lt;sup&gt;c&lt;/sup&gt;</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15-Year LM &amp; SNF Experience</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual Fixed Effects</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Wage Level in 1993 (EUR)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>80.14</td>
<td>80.14</td>
<td>93.23</td>
<td>93.23</td>
</tr>
<tr>
<td>S.D.</td>
<td>8.18</td>
<td>8.18</td>
<td>7.05</td>
<td>7.05</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>14,490</td>
<td>14,490</td>
<td>32,844</td>
<td>32,844</td>
</tr>
</tbody>
</table>

<sup>a</sup> “New Hires” are individuals who were not employed in a SNF in the year before each index year.

<sup>b</sup> SNF “Incumbents” are SNF employees who are not new hires.

<sup>c</sup> Control variables in column (2) are county-year-level means of residuals from individual-year-level regressions of log wage on 15-Year Rolling Labor Market and SNF Experience. Control variables in column (4) are county-year-level mean of residuals from a regression of log wage on worker fixed effects.

Notes: The top panel displays the pooled coefficient $\delta_{97-08}$, obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using $E_r$, derived in Equation 1, as the measure of a county’s exposure to the reform. The outcome variable in all columns is log of daily wage in constant 2020 Euros. The second panel displays $\lambda_t$ coefficients of the event study in Equation 2. Coefficients were normalized to zero in year $t = 1993$. All specifications include county and year fixed effects. Standard errors clustered at the county-level are reported in parentheses.
Table 4: Event Study Results: Characteristics of New SNF Hires

<table>
<thead>
<tr>
<th>Outcome (Among New SNF Hires(^a))</th>
<th>Age</th>
<th>Share German</th>
<th>Share Female</th>
<th>Share Abitur</th>
<th>15-Year LM Exp(^b)</th>
<th>15-Year SNF Exp(^b)</th>
<th>In Health-care in t-1 (^c)</th>
<th>Unemployed in t-1 (^c)</th>
<th>UE Duration During 3 Pre-Hire Years</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pooled Coefficients</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\delta_{97-08})</td>
<td>-1.06</td>
<td>0.05</td>
<td>0.04</td>
<td>-0.13</td>
<td>-3.54</td>
<td>-0.40</td>
<td>-0.07</td>
<td>0.12</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>(1.56)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.04)</td>
<td>(0.71)</td>
<td>(0.38)</td>
<td>(0.07)</td>
<td>(0.05)</td>
<td>(0.11)</td>
</tr>
<tr>
<td><strong>Event Study Results</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Year Effect, (\lambda_{1997})</td>
<td>-0.97</td>
<td>0.03</td>
<td>0.12</td>
<td>-0.01</td>
<td>-2.48</td>
<td>-0.91</td>
<td>-0.09</td>
<td>0.26</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>(1.92)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(1.00)</td>
<td>(0.47)</td>
<td>(0.11)</td>
<td>(0.07)</td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>3-Year Effect, (\lambda_{2000})</td>
<td>-1.13</td>
<td>0.06</td>
<td>0.04</td>
<td>-0.05</td>
<td>-2.42</td>
<td>-0.62</td>
<td>-0.01</td>
<td>0.09</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>(1.65)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.87)</td>
<td>(0.47)</td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>5-Year Effect, (\lambda_{2001})</td>
<td>-2.60</td>
<td>0.05</td>
<td>0.05</td>
<td>-0.06</td>
<td>-4.00</td>
<td>-0.87</td>
<td>-0.03</td>
<td>0.05</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>(1.80)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.90)</td>
<td>(0.43)</td>
<td>(0.08)</td>
<td>(0.06)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>8-Year Effect, (\lambda_{2004})</td>
<td>0.80</td>
<td>0.05</td>
<td>0.03</td>
<td>-0.14</td>
<td>-2.95</td>
<td>-0.20</td>
<td>-0.02</td>
<td>0.11</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>(2.29)</td>
<td>(0.04)</td>
<td>(0.07)</td>
<td>(0.94)</td>
<td>(0.53)</td>
<td>(0.11)</td>
<td>(0.07)</td>
<td>(0.15)</td>
<td></td>
</tr>
<tr>
<td><strong>Implied Impact</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using In-sample Variation(^d)</td>
<td>-0.10</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.01</td>
<td>-0.32</td>
<td>-0.04</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td><strong>Level of Outcome in 1993</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>35.14</td>
<td>0.91</td>
<td>0.83</td>
<td>0.09</td>
<td>4.71</td>
<td>1.02</td>
<td>0.19</td>
<td>0.17</td>
<td>0.36</td>
</tr>
<tr>
<td>S.D.</td>
<td>1.60</td>
<td>0.08</td>
<td>0.06</td>
<td>0.05</td>
<td>0.82</td>
<td>0.38</td>
<td>0.07</td>
<td>0.07</td>
<td>0.16</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>10,620</td>
<td>10,620</td>
<td>10,620</td>
<td>10,620</td>
<td>6,118</td>
<td>6,118</td>
<td>10,620</td>
<td>9,332</td>
<td>8,690</td>
</tr>
</tbody>
</table>

\(^a\) “New Hires” are individuals who were not employed in a SNF in the year before each index year.

\(^b\) Outcomes in columns (5) and (6) are county-level means of the sum of years, measured throughout a rolling retrospective 15-year window, of labor market experience of new SNF hires, with index years restricted to 1990 through 2008.

\(^c\) Restricted to years 1976 through 2004 due to the introduction of ALG-II unemployment benefits in 2005.

\(^d\) Multiplies \(\delta_{97-08}\) by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure.

Notes: The top panel displays the pooled coefficient \(\delta_{97-08}\), obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using \(E_r\), derived in Equation 1, as the measure of a county’s exposure to the reform. The outcome variables are demographic or labor market experience of new hires, as specified in column titles. The second panel displays \(\lambda_t\) coefficients of the event study in Equation 2. Coefficients were normalized to zero in year \(t = 1993\). All specifications include county and year fixed effects. Standard errors clustered at the county-level are reported in parentheses.
Table 5: Event Study Results: Old-Age Mortality

<table>
<thead>
<tr>
<th></th>
<th>Outcome: Deaths per 100 in 75+ population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variation in $E_r$</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>Pooled Coefficients</strong></td>
<td></td>
</tr>
<tr>
<td>$\delta_{97-08}$</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td>(0.75)</td>
</tr>
<tr>
<td><strong>Event Study Results</strong></td>
<td></td>
</tr>
<tr>
<td>1-Year Effect, $\lambda_{1997}$</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(0.69)</td>
</tr>
<tr>
<td>3-Year Effect, $\lambda_{1999}$</td>
<td>-0.86</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
</tr>
<tr>
<td>5-Year Effect, $\lambda_{2001}$</td>
<td>-0.81</td>
</tr>
<tr>
<td></td>
<td>(0.89)</td>
</tr>
<tr>
<td><strong>Implied Impact</strong></td>
<td></td>
</tr>
<tr>
<td>Using In-sample Variation$^a$</td>
<td>-0.01</td>
</tr>
<tr>
<td>Aggregate Impact, West Germany$^b$</td>
<td>-318.15</td>
</tr>
<tr>
<td>Using Out-of-sample Variation$^c$</td>
<td>-0.07</td>
</tr>
<tr>
<td>Aggregate Impact, West Germany$^b$</td>
<td>-2,426</td>
</tr>
<tr>
<td><strong>Level of Outcome in 1993</strong></td>
<td></td>
</tr>
<tr>
<td>Mean$^d$</td>
<td>10.01</td>
</tr>
<tr>
<td>S.D.</td>
<td>0.88</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>5,238</td>
</tr>
</tbody>
</table>

$^a$ Multiplies $\delta_{97-08}$ by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure.

$^b$ Multiplies per (100) capita impact by 33,818.89 in (1) and 43,154.29 in (2), which measures the number of people age 75+ in West Germany in 1993 in hundreds, excluding Berlin and Bremen in (1) and including in (2).

$^c$ Multiplies $\delta_{97-08}$ by the mean of the exposure variable across counties, $E_r = 0.686$.

$^d$ The mean level of the outcome in (2) is for West Germany only, as obtained from the Human Mortality Database, and includes all counties.

Notes: Column (1) displays the results of estimating equations 2 and 3 for older age (population age 75+) mortality as an outcome, using $E_r$, derived in 1, as the measure of exposure to LTC insurance expansion. $\lambda_t$ coefficients have been normalized to year $t = 1993$. Column (2) displays coefficients from the synthetic control procedure (Abadie et al., 2010). The pooled coefficient is defined as the average difference in the mortality rate, for the population age 75 and above, between West Germany and synthetic West Germany from $t = 1997$ to $t = 2008$. Standard errors, clustered at the county-level, are reported in parentheses in (1), p-values, from permutation-based inference following Abadie et al. (2010), are reported in square brackets in (2). Data source in (1) are the statistical agencies of West German federal states, excluding Bremen and Berlin. Data source in (2) is the Human Mortality Database.
Table 6: Characteristics of Workers “At Risk” of Being a SNF Hire

<table>
<thead>
<tr>
<th>Predicted Hiring Risk</th>
<th>SNF in t &amp;</th>
<th>5-Year-Lagged Predictors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Risk ≥ 0%</td>
<td>Risk ≥ 0.25%</td>
<td>Risk ≥ 0.5%</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>5-Year-Lagged Predictors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (in year t-5)</td>
<td>36.13</td>
<td>34.36</td>
<td>34.45</td>
</tr>
<tr>
<td>% Female (in year t-5)</td>
<td>41.26</td>
<td>67.13</td>
<td>96.65</td>
</tr>
<tr>
<td>% German (in year t-5)</td>
<td>87.94</td>
<td>79.93</td>
<td>82.02</td>
</tr>
<tr>
<td>% University Education (in year t-5)</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>% High School Equivalent (in year t-5)</td>
<td>0.07</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>% Employed in Medical Sector (in year t-5)</td>
<td>5.72</td>
<td>15.02</td>
<td>21.17</td>
</tr>
<tr>
<td>% Unemployed (in year t-5)</td>
<td>4.30</td>
<td>11.98</td>
<td>7.03</td>
</tr>
<tr>
<td>Outcome</td>
<td>0.56</td>
<td>1.32</td>
<td>1.70</td>
</tr>
</tbody>
</table>

| No. of Observations | 48,102,814 | 17,269,693 | 11,832,155 | 7,171,159 | 5,914,736 | 157,498 |

Notes: The top panel of this table displays averages of variables used to estimate SNF hiring probabilities, by predicted hiring risk, for a 10% draw from the annualized universe of labor market biographies for years 1980-2004, restricted to individuals over 25 who did not have a history of SNF employment five years before each index year. The second panel displays the realized SNF hiring probabilities, again by predicted hiring risk. The sample underlying each column is a strict subset of the sample underlying the column to the left, with predicted hiring probability (“Risk”) increasing in column count. Summary statistics, measured in year t, for the “Labor Market Sample” underlying column (1), are displayed in column (3) of Table 1. Details on the classification tree model used to estimate hiring risks and predictor coding are in Appendix Section C.
Table 7: Event Study Results on “At Risk” Workers (Predicted Hiring Risk ≥ 1%)

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Regular Employment in</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SNF (1)</td>
<td>Hospitals (2)</td>
<td>Other Healthcare (3)</td>
<td>Unemployment (4)</td>
</tr>
<tr>
<td><strong>Pooled Coefficients</strong></td>
<td>δ_{97-08}</td>
<td>0.026</td>
<td>-0.004</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.013)</td>
<td>(0.020)</td>
<td>(0.015)</td>
</tr>
<tr>
<td><strong>Event Study Coefficients</strong></td>
<td>1-Year Effect, λ_{1997}</td>
<td>0.010</td>
<td>0.009</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.015)</td>
<td>(0.019)</td>
<td>(0.015)</td>
</tr>
<tr>
<td></td>
<td>3-Year Effect, λ_{1999}</td>
<td>0.022</td>
<td>-0.005</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.015)</td>
<td>(0.023)</td>
<td>(0.016)</td>
</tr>
<tr>
<td></td>
<td>5-Year Effect, λ_{2001}</td>
<td>0.024</td>
<td>0.004</td>
<td>-0.020</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.015)</td>
<td>(0.022)</td>
<td>(0.016)</td>
</tr>
<tr>
<td></td>
<td>10-Year Effect, λ_{2004}</td>
<td>0.037</td>
<td>-0.011</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.015)</td>
<td>(0.024)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>Implied Impact</strong></td>
<td>Using In-sample Variation^a</td>
<td>0.002</td>
<td>-0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>Aggregate Impact, West Germany^b</td>
<td>6,446</td>
<td>-1,014</td>
<td>-3,449</td>
</tr>
<tr>
<td></td>
<td>Using Out-of-sample Variation^c</td>
<td>0.018</td>
<td>-0.003</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>Aggregate Impact, West Germany^b</td>
<td>48,720</td>
<td>-7,665</td>
<td>-26,069</td>
</tr>
</tbody>
</table>

**Level of Outcome in 1993**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>0.026</th>
<th>0.092</th>
<th>0.049</th>
<th>0.057</th>
</tr>
</thead>
<tbody>
<tr>
<td>S.D.</td>
<td>0.012</td>
<td>0.041</td>
<td>0.018</td>
<td>0.021</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Observations</td>
<td>8,050</td>
<td>8,050</td>
<td>8,050</td>
<td>8,050</td>
<td>8,050</td>
</tr>
</tbody>
</table>

^a Multiplies δ_{97-08} by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure

^b We compute aggregate impact of the reform by multiplying the per capita impact with 277,343, which is the number of underlying individual-year-level observations with a predicted risk of hiring ≥ 1% in 1993.

^c Multiplies δ_{97-08} by the mean of the exposure variable across counties, E_r = 0.686.

Notes: The top panel displays the pooled coefficient δ_{97-08}, obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using E_r, derived in Equation 1, as the measure of a county’s exposure to the reform. Outcome variables are the share of individuals employed in a SNF, a hospital, or another healthcare firm (columns 1-3) or unemployed (column 4). The second panel displays λ_t coefficients of the event study in Equation 2. Coefficients were normalized to zero in year t = 1993. All specifications include county and year fixed effects. Standard errors clustered at the county-level are reported in parentheses. Underlying data is the subset of observations in the “Labor Market Sample”, with a predicted SNF hiring probability ≥ 1%. Hiring probabilities were estimated using the classification tree model outlined in Appendix Section C, with further details displayed in A.9.
Notes: The share of individuals in need of long-term care, who did not have means-tested support for long-term care services in 1993, prior to 1995-1996 rollout of universal LTC insurance. The measure, denoted with $E_r$, throughout the text is derived in Equation (1). We maps shows $E_r$ for 322 West German counties in 15 exposure regions, excluding Berlin and Bremen.
Figure A.2: Relationship between Baseline and Alternative Measures of Exposure to the Reform

(A) Baseline and Alternative Measure (I)  
(B) Baseline and Alternative Measure (II)

(C) Alternative Measures (I) and (II)

Notes: Displayed are scatter plots of measures of exposure to the LTC insurance reform. The “Baseline Exposure Measure”, denoted with $E_r$ throughout the text, is derived in Equation (1) and measures the share of individuals in need of long-term care, who did not have means-tested support for long-term care services in 1993, prior to the 1995-1996 rollout of universal LTC insurance (mean of $E_r = 0.686$). The “Alternative Exposure Measure I” is defined as $E_r = 100\% - \frac{H_{55andOlderPopulationr,1993}}{9_{55andOlderPopulationr,1993} \times \text{LTCClaims}_{r,1995} \times H_{55andOlderPopulationr,1993}}$ (mean of $E_r = 0.953$) and “Alternative Exposure Measure II” as $E_r = \frac{9_{55andOlderPopulationr,1993} \times \text{LTCClaims}_{r,1995} - H_{55andOlderPopulationr,1993}}{65andOlderPopulationr,1993}$ (mean of $E_r = 0.103$). The slope coefficient of the regression line displayed in panel A.2A is 0.158 (standard error 0.004), the slope of the line in A.2B is 0.154 (s.e. 0.009), and the slope in A.2C is 0.501 (s.e. 0.065). All three measures vary across 15 different West German geographical regions. Figure A.1 displays the variation of the “Baseline Exposure Measure” across geographies.
Notes: Displayed are scatter plots of the baseline measure of exposure to the LTC insurance reform and 1995 per capita income in EUR at the exposure-region-level. The baseline exposure measure, denoted with $E_r$ throughout the text, is derived in Equation (1) and measures the share of individuals in need of long-term care, who did not have means-tested support for long-term care services in 1993, prior to the 1995-1996 rollout of universal LTC insurance (mean of $E_r = 0.686$). This measure varies across 15 different West German geographical regions, visualized in Figure A.1. The correlation of the baseline exposure measure with income per capita, visualized in A.3A, is statistically insignificant at $p = 0.991$, and the correlation with disposable income, displayed in in A.3B, is statistically insignificant at $p = 0.993$. Income data have been obtained from (Statistische Ämter des Bundes und der Länder, 2021a).
Figure A.4: Universal LTC Insurance and Supply of SNF Care, by Type of Employment

(A) Full-Time Workers per 1,000 65+ Population

(B) Part-Time Workers per 1,000 65+ Population

(C) Full-Time Workers, Event Study

(D) Part-Time Workers, Event Study

Notes: The top panels plot the average—across counties—number of SNF full-time (panel A) and part-time (panel B) workers per 1,000 individuals age 65+ and over, in 1975-2008. The county-level average is computed separately for the group of West German counties with (region-level) exposure variable $E_r$ above and below the median across counties. All counties at the median are assigned to the below median group. Both time-series are normalized to the aggregate mean across all counties in 1993. Panels C and D display $\lambda_t$ coefficients and 95% confidence intervals from estimating the specification in Equation 2 with the number of full-time (panel C) or part-time (panel D) workers as an outcome. Coefficients $\lambda_t$ were normalized to zero in the pre-reform year $t = 1993$. $\lambda_t$ multiply the exposure variable $E_r$ that takes values from 0 to 1 and measures the share of potential long-term care patients who did not have public assistance for LTC prior to the rollout of universal LTC insurance (mean of $E_r$=0.686). The geographic variation in $E_r$ is visualized in Figure A.1. The mean of outcome variables in 1993 is reported in Table 2.
Figure A.5: Introduction of Universal LTC Insurance and Supply of SNF Care: Alternative Specifications

I. Baseline Specification at Region $r$ Level, at which Exposure $E_r$ varies

(A) SNF Firms

(B) SNF Workers

(C) SNF Full-Time Workers

(D) SNF Part-Time Workers

II. County-Specific Time Trend

(E) SNF Firms

(F) SNF Workers

(G) SNF Full-Time Workers

(H) SNF Part-Time Workers

Notes: All panels display $\lambda_t$ coefficients and 95% confidence intervals from estimating variations—as specified above the panels—of the specification in Equation 2 with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients $\lambda_t$ were normalized to zero in the pre-reform year $t = 1993$. $\lambda_t$ multiply the exposure variable $E_r$ that takes values from 0 to 1 and measures the share of potential long-term care patients who did not have public assistance for LTC prior to the rollout of universal LTC insurance (mean of $E_r=0.686$). The geographic variation in $E_r$ is visualized in Figure A.1. The mean of outcome variables in 1993 is reported in Table A1.
III. S.E. Clustered at Region \( r \) Level, at which Exposure \( E_r \) varies

(A) SNF Firms  
(B) SNF Workers  
(C) SNF Full-Time Workers  
(D) SNF Part-Time Workers

IV. Binary Exposure Measure

(E) SNF Firms  
(F) SNF Workers  
(G) SNF Full-Time Workers  
(H) SNF Part-Time Workers

Notes: All panels display \( \lambda_t \) coefficients and 95% confidence intervals from estimating the specification in Equation 2, with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients \( \lambda_t \) were normalized to zero in the pre-reform year \( t = 1993 \). The geographic variation in \( E_r \) is visualized in Figure A.1. The bottom panel uses an alternative measures of exposure to the reform, which takes on the value of one for counties above the median of the exposure measure derived in Equation 1, and zero otherwise (mean of 0.410). The mean of outcome variables in 1993 is reported in Tables A1 and A2.
V. Alternative Exposure Measure (I): \( E_r = 100\% - \frac{H_{zP_r,1993}}{65\text{andOlderPopulation}_{r,1993}} \).

VI. Alternative Exposure Measure (II): \( E_r = \frac{g_{r,1993,1999}\times LTCClaims_{r,1999}-H_{zP_r,1993}}{65\text{andOlderPopulation}_{r,1993}} \).

Notes: All panels display \( \lambda_t \) coefficients and 95% confidence intervals from estimating the specification in Equation 2 with alternative measures of exposure to the reform, with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients \( \lambda_t \) were normalized to zero in the pre-reform year \( t = 1993 \). The alternative exposure measure (I) is defined as \( E_r = 100\% - \frac{H_{zP_r,1993}}{65\text{andOlderPopulation}_{r,1993}} \) (mean of \( E_r = 0.953 \)). The alternative exposure measure (II) is defined as \( E_r = \frac{g_{r,1993,1999}\times LTCClaims_{r,1999}-H_{zP_r,1993}}{65\text{andOlderPopulation}_{r,1993}} \) (mean of \( E_r = 0.103 \)). The mean of outcome variables in 1993 is reported in Table A2.
VII. Controlling for the County-Year-Level Count of Elderly

(A) SNF Firms
(B) SNF Workers
(C) SNF Full-Time Workers
(D) SNF Part-Time Workers

VIII. Controlling for the County-Year-Level Share of Elderly

(E) SNF Firms
(F) SNF Workers
(G) SNF Full-Time Workers
(H) SNF Part-Time Workers

Notes: All panels display $\lambda_t$ coefficients and 95% confidence intervals from estimating variations—as specified above the panels—of the specification in Equation 2 with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients $\lambda_t$ were normalized to zero in the pre-reform year $t = 1993$. $\lambda_t$ multiply the exposure variable $E_r$ that takes values from 0 to 1 and measures the share of potential long-term care patients who did not have public assistance for LTC prior to the rollout of universal LTC insurance (mean of $E_r=0.686$). The geographic variation in $E_r$ is visualized in Figure A.1. The mean of outcome variables in 1993 is reported in Table A3.
Notes: Panel A plots the cumulative distribution functions of predicted SNF hiring probabilities separately for the population “at-risk” of being hired into SNF and the population of realized SNF hires. Panel B displays the importance of each predictor, with values standardized to sum to 100. Panel C plots the out-of-sample $R^2$ against the complexity parameter. The $R^2$ is maximized at a complexity parameter of 0.00001396.
 Table A1: Event Study Results: Aggregate Response, Alternative Specifications

<table>
<thead>
<tr>
<th></th>
<th>At Exposure Region Level</th>
<th>County-Specific Time Trend</th>
<th>S.E. Clustered at Region r level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td>Firms (1)</td>
<td>Workers (2)</td>
<td>Full-time (3)</td>
</tr>
<tr>
<td>Pooled Coefficients</td>
<td>δ &lt;sub&gt;97-08&lt;/sub&gt;</td>
<td>0.57</td>
<td>53.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.26)</td>
<td>(15.08)</td>
</tr>
<tr>
<td>Event Study Coefficients</td>
<td>1-Year Effect, λ&lt;sub&gt;1997&lt;/sub&gt;</td>
<td>0.28</td>
<td>26.36</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.26)</td>
<td>(8.51)</td>
</tr>
<tr>
<td></td>
<td>3-Year Effect, λ&lt;sub&gt;1999&lt;/sub&gt;</td>
<td>0.29</td>
<td>48.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.36)</td>
<td>(10.25)</td>
</tr>
<tr>
<td></td>
<td>5-Year Effect, λ&lt;sub&gt;2001&lt;/sub&gt;</td>
<td>0.41</td>
<td>56.58</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.37)</td>
<td>(20.03)</td>
</tr>
<tr>
<td></td>
<td>10-Year Effect, λ&lt;sub&gt;2006&lt;/sub&gt;</td>
<td>0.90</td>
<td>58.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.26)</td>
<td>(15.20)</td>
</tr>
<tr>
<td>Implied Impact</td>
<td>Using In-sample Variation&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.06</td>
<td>5.54</td>
</tr>
<tr>
<td></td>
<td>Aggregate Impact, West Germany&lt;sup&gt;b&lt;/sup&gt;</td>
<td>574.49</td>
<td>53,701</td>
</tr>
<tr>
<td></td>
<td>Using Out-of-sample Variation&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.40</td>
<td>37.78</td>
</tr>
<tr>
<td></td>
<td>Aggregate Impact, West Germany&lt;sup&gt;c&lt;/sup&gt;</td>
<td>3,918</td>
<td>366,270</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level of Outcome in 1993</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.76</td>
<td>31.44</td>
<td>22.84</td>
<td>8.60</td>
<td>0.74</td>
<td>31.98</td>
<td>23.11</td>
<td>8.87</td>
<td>0.78</td>
<td>31.98</td>
<td>23.11</td>
<td>8.87</td>
</tr>
<tr>
<td>S.D.</td>
<td>0.17</td>
<td>5.54</td>
<td>4.01</td>
<td>2.00</td>
<td>0.31</td>
<td>13.98</td>
<td>10.11</td>
<td>4.52</td>
<td>0.33</td>
<td>13.98</td>
<td>10.11</td>
<td>4.52</td>
</tr>
</tbody>
</table>

<sup>a</sup> Multiplies δ<sub>97-08</sub> by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure.

<sup>b</sup> Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.

<sup>c</sup> Multiplies δ<sub>97-08</sub> by the mean of the exposure variable across counties, E_r = 0.686.

Notes: The top panel displays the pooled coefficient δ<sub>97-08</sub>, obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using E_r, derived in Equation 1, as the measure of a county’s exposure to the reform. Outcome variables include the number of SNF firms and the number of regular SNF workers, in total, part-time and full-time, per 1,000 individuals age 65 and older. See Appendix B.2 for the definition of a SNF and a “regular” worker in SNF. The second panel displays λ_t coefficients of the event study in Equation 2. Coefficients were normalized to zero in year t = 1993. All specifications include county and year fixed effects. Columns (1)-(4) also include county-specific time trend. Standard errors clustered at the county-level (columns 1-4) and at the region r level (columns 5-8) are included in parentheses.
Table A2: Event Study Results: Aggregate Response, Alternative Specifications

<table>
<thead>
<tr>
<th>Outcome (per 1,000 Age 65+ Population)</th>
<th>Binary Exposure Measure</th>
<th>Alternative Exposure Measure (I)</th>
<th>Alternative Exposure Measure (II)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
<td>(9) (10) (11) (12)</td>
</tr>
<tr>
<td><strong>Event Study Results</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pooled Coefficients</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>δ_{97−08}</td>
<td>0.05 5.97 3.11 2.86</td>
<td>1.32 19.12 84.17 109.12</td>
<td>3.57 211.26 118.20 93.06</td>
</tr>
<tr>
<td>(0.02) (0.97) (0.59) (0.59)</td>
<td>(0.44) (45.57) (27.39)</td>
<td>(20.91)</td>
<td>(0.58) (40.23) (25.87) (22.20)</td>
</tr>
<tr>
<td>Event Study Coefficients</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Year Effect, λ_{1997}</td>
<td>0.03 3.80 2.18 1.62</td>
<td>0.64 17.72 49.93 67.79</td>
<td>2.56 108.15 72.69 35.46</td>
</tr>
<tr>
<td>(0.02) (0.82) (0.51) (0.41)</td>
<td>(0.75) (37.19) (25.26)</td>
<td>(17.98)</td>
<td>(0.56) (35.02) (22.75) (15.96)</td>
</tr>
<tr>
<td>3-Year Effect, λ_{1999}</td>
<td>0.03 4.89 2.85 2.04</td>
<td>0.55 14.29 72.16 75.13</td>
<td>2.87 102.85 108.93 53.92</td>
</tr>
<tr>
<td>(0.02) (0.93) (0.57) (0.51)</td>
<td>(0.82) (44.54) (27.06)</td>
<td>(22.99)</td>
<td>(0.63) (38.75) (25.19) (19.08)</td>
</tr>
<tr>
<td>5-Year Effect, λ_{2001}</td>
<td>0.04 5.78 3.40 2.86</td>
<td>0.46 184.19 98.43 85.97</td>
<td>3.31 206.84 130.57 76.27</td>
</tr>
<tr>
<td>(0.02) (1.06) (0.65) (0.59)</td>
<td>(0.92) (49.05) (30.21)</td>
<td>(26.68)</td>
<td>(0.73) (42.11) (28.06) (21.81)</td>
</tr>
<tr>
<td>10-Year Effect, λ_{2006}</td>
<td>0.07 6.77 3.11 3.67</td>
<td>2.50 230.58 83.23 147.36</td>
<td>4.30 251.61 120.53 131.09</td>
</tr>
<tr>
<td>(0.02) (1.13) (0.70) (0.75)</td>
<td>(1.04) (52.16) (31.97)</td>
<td>(33.80)</td>
<td>(0.78) (44.95) (29.10) (28.10)</td>
</tr>
<tr>
<td>Implied Impact</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using In-sample Variation**</td>
<td>0.05 5.97 3.11 2.86</td>
<td>0.02 2.87 1.25 1.63</td>
<td>0.08 4.49 2.51 1.97</td>
</tr>
<tr>
<td>Aggregate Impact, West Germany**</td>
<td>472.69 57,496 30,173 27,723</td>
<td>194.19 27,846 12,126 15,802</td>
<td>733.61 43,568 24,377 19,101</td>
</tr>
<tr>
<td>Level of Outcome in 1993</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.78 31.98 23.11 8.87</td>
<td>0.78 31.98 23.11 8.87</td>
<td>0.78 31.98 23.11 8.87</td>
</tr>
<tr>
<td>S.D.</td>
<td>0.33 13.06 10.11 4.52</td>
<td>0.33 13.06 10.11 4.52</td>
<td>0.33 13.06 10.11 4.52</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>10,635 10,948 10,948 10,948 10,948 10,948 10,948 10,948 10,948 10,948 10,948</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- The binary exposure measure takes on the value of one for counties above the median of the exposure measure $E_r$ derived in Equation 1, and zero otherwise.
- The alternative exposure measure (I) is defined as $E_r = 100\% - \frac{HzP_{1993} \cdot 65\text{ and Older Population}_{1993}}{65\text{ and Older Population}_{1993}}$. 
- The alternative exposure measure (II) is defined as $E_r = \frac{g_{1993, 1999} \cdot LTCClaims_{1999} - HzP_{1993} \cdot 65\text{ and Older Population}_{1993}}{65\text{ and Older Population}_{1993}}$. 
- The “In-sample impact” of the reform on the per capita outcome of interest uses variation in exposure across regions. We multiply $\delta_{97−08}$ with the difference in mean exposure (1 for the “Binary Exposure Measure”, 0.015 for the “Alternative Exposure Measure (I)”, and 0.021 for the “Alternative Exposure Measure (II)”) between counties with above median exposure and those with below median exposure.
- Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.

Notes: The top panel displays the pooled coefficient $\delta_{97−08}$, obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using either a binary version of $E_r$, derived in Equation 1, as the measure of a county’s exposure to the reform (columns 1-4), or a simplified version of $E_r$ computed using age 65+ population as the measure of potential demand for LTC rather than the number of LTC insurance claimants (columns 5-8), or an alternative exposure measure exploiting variation in the difference between the count of LTC insurance beneficiaries and beneficiaries from the means tested HzP program (columns 9-12). Outcome variables include the number of SNF firms and the number of regular SNF workers, in total, part-time and full-time, per 1,000 individuals age 65 and older. See Appendix B.2 for the definition of a SNF and a “regular” worker in SNF. The second panel displays $\lambda_t$ coefficients of the event study in Equation 2. Coefficients were normalized to zero in year $t = 1993$. All specifications include county and year fixed effects. Standard errors clustered at the county-level are reported in parentheses.
Table A3: Event Study Results: Aggregate Response, Alternative Specifications

<table>
<thead>
<tr>
<th></th>
<th>Outcome (per 1,000 Age 65+ Population)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Controlling for Count of Elderly</td>
<td>Controlling for Share of Elderly</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Firms Workers Full-time Part-time</td>
<td>Firms Workers Full-time Part-time</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
<td></td>
</tr>
<tr>
<td>Pooled Coefficients</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\delta_{t=08} )</td>
<td>0.32</td>
<td>32.43</td>
<td>17.53</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(8.43)</td>
<td>(5.06)</td>
</tr>
<tr>
<td>Event Study Coefficients</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Year Effect, (\lambda_{1997} )</td>
<td>0.28</td>
<td>22.34</td>
<td>12.13</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(6.89)</td>
<td>(4.34)</td>
</tr>
<tr>
<td>3-Year Effect, (\lambda_{1999} )</td>
<td>0.27</td>
<td>29.26</td>
<td>17.66</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(8.16)</td>
<td>(4.96)</td>
</tr>
<tr>
<td>5-Year Effect, (\lambda_{2001} )</td>
<td>0.24</td>
<td>34.41</td>
<td>21.70</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(8.97)</td>
<td>(5.54)</td>
</tr>
<tr>
<td>10-Year Effect, (\lambda_{2006} )</td>
<td>0.43</td>
<td>33.90</td>
<td>14.78</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(9.94)</td>
<td>(6.02)</td>
</tr>
<tr>
<td>Implied Impact</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using In-sample Variation(^a)</td>
<td>0.03</td>
<td>2.95</td>
<td>1.59</td>
</tr>
<tr>
<td>Aggregate Impact, West Germany(^b)</td>
<td>281.10</td>
<td>28,551</td>
<td>15,436</td>
</tr>
<tr>
<td>Using Out-of-sample Variation(^c)</td>
<td>0.22</td>
<td>22.26</td>
<td>12.03</td>
</tr>
<tr>
<td>Aggregate Impact, West Germany(^b)</td>
<td>2,098</td>
<td>215,784</td>
<td>116,661</td>
</tr>
<tr>
<td>Level of Outcome in 1993</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.78</td>
<td>31.98</td>
<td>23.11</td>
</tr>
<tr>
<td>S.D.</td>
<td>0.33</td>
<td>13.58</td>
<td>10.11</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>10,635</td>
<td>10,948</td>
<td>10,948</td>
</tr>
</tbody>
</table>

\(^a\) Multiplies \(\delta_{t=08} \) by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure.

\(^b\) Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.

\(^c\) Multiplies \(\delta_{t=08} \) by the mean of the exposure variable across counties, \(E_r = 0.686\).

Notes: The top panel displays the pooled coefficient \(\delta_{t=08} \), obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using \(E_r \), derived in Equation 1, as the measure of a county’s exposure to the reform. Outcome variables include the number of SNF firms and the number of regular SNF workers, in total, part-time and full-time, per 1,000 individuals age 65 and older. See Appendix B.2 for the definition of a SNF and a “regular” worker in SNF. The second panel displays \(\lambda_t \) coefficients of the event study in Equation 2. Coefficients were normalized to zero in year \(t = 1993\). Columns 1-4 display results of specifications controlling for the county-year-level count of individuals age 65 and above, columns 5-8 control for the county-year-level population share of residents age 65 and above. All specifications include county and year fixed effects. Standard errors clustered at the county-level are included in parentheses.
Table A4: Event Study Results: Count of New SNF Hires By Origin

<table>
<thead>
<tr>
<th></th>
<th>Count New SNF Hires</th>
<th>Among New SNF Hires</th>
<th>Count of</th>
<th>Employed &amp;</th>
<th>Employed &amp;</th>
<th>Unemployed</th>
<th>Temporarily Not in</th>
<th>Not Yet in</th>
<th>Data in t-1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pooled Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_{97-08}$</td>
<td>8.69</td>
<td>0.67</td>
<td>1.16</td>
<td>2.04</td>
<td>3.83</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.92)</td>
<td>(0.75)</td>
<td>(0.58)</td>
<td>(0.43)</td>
<td>(0.53)</td>
<td>(0.42)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Event Study Results</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Year Effect, $\lambda_{1997}$</td>
<td>8.74</td>
<td>3.19</td>
<td>0.23</td>
<td>2.48</td>
<td>2.43</td>
<td>0.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.28)</td>
<td>(3.23)</td>
<td>(0.89)</td>
<td>(0.60)</td>
<td>(0.54)</td>
<td>(0.49)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-Year Effect, $\lambda_{1999}$</td>
<td>6.75</td>
<td>0.01</td>
<td>1.35</td>
<td>1.76</td>
<td>2.95</td>
<td>0.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.16)</td>
<td>(0.80)</td>
<td>(0.65)</td>
<td>(0.58)</td>
<td>(0.67)</td>
<td>(0.49)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-Year Effect, $\lambda_{2001}$</td>
<td>9.11</td>
<td>-0.27</td>
<td>2.32</td>
<td>2.06</td>
<td>3.45</td>
<td>1.55</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.33)</td>
<td>(1.03)</td>
<td>(0.72)</td>
<td>(0.53)</td>
<td>(0.71)</td>
<td>(0.47)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10-Year Effect, $\lambda_{2006}$</td>
<td>8.98</td>
<td>1.31</td>
<td>0.69</td>
<td>2.30</td>
<td>3.49</td>
<td>1.20</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.25)</td>
<td>(1.03)</td>
<td>(0.71)</td>
<td>(0.51)</td>
<td>(0.62)</td>
<td>(0.54)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implied Impact</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using In-sample Variation$^a$</td>
<td>0.79</td>
<td>0.06</td>
<td>0.11</td>
<td>0.19</td>
<td>0.35</td>
<td>0.09</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregate Impact, West Germany$^b$</td>
<td>7.651</td>
<td>586</td>
<td>1.020</td>
<td>1.798</td>
<td>3.370</td>
<td>877</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using Out-of-sample Variation$^c$</td>
<td>5.97</td>
<td>0.46</td>
<td>0.80</td>
<td>1.40</td>
<td>2.63</td>
<td>0.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregate Impact, West Germany$^b$</td>
<td>57.826</td>
<td>4.430</td>
<td>7.707</td>
<td>13.590</td>
<td>25.474</td>
<td>6.625</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level of Outcome in 1993</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>6.44</td>
<td>1.00</td>
<td>1.33</td>
<td>1.10</td>
<td>1.98</td>
<td>1.03</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S.D.</td>
<td>2.80</td>
<td>0.72</td>
<td>0.81</td>
<td>0.62</td>
<td>0.90</td>
<td>0.61</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of Observations</td>
<td>10,626</td>
<td>10,626</td>
<td>10,626</td>
<td>10,626</td>
<td>10,626</td>
<td>10,626</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^a$ “New Hires” are individuals who were not employed in a SNF in the year before each index year.

$^b$ Multiplies $\delta_{97-08}$ by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure.

$^c$ Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.

$^d$ Multiplies $\delta_{97-08}$ by the mean of the exposure variable across counties, $E_r = 0.686$.

Notes: The top panel displays the pooled coefficient $\delta_{97-08}$, obtained from estimating the difference in differences specification in Equation 3 at the county-year level, using $E_r$, derived in Equation 1, as the measure of a county’s exposure to the reform. The outcome variables are demographic or labor market experience of new hires, as specified in column titles. The second panel displays $\lambda_t$ coefficients of the event study in Equation 2. Coefficients were normalized to zero in year $t = 1993$. All specifications include county and year fixed effects. Standard errors clustered at the county-level are reported in parentheses.
Table A5: Event Study Results: Count of New SNF Hires By Characteristics

<table>
<thead>
<tr>
<th>Outcome (per 1,000 Age 65+ Population)</th>
<th>Count of New SNF Hires</th>
<th>Among New SNF Hires, Count of</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Abitur Holders</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Germans</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Females</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Part-time Employees</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Apprentices in t-1</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>(5)</td>
<td>(6)</td>
</tr>
</tbody>
</table>

Pooled Coefficients

| δ_{97-08} | (1.92) |
| 8.69      | 0.28   |
| 8.33      | (1.74) |
| 7.54      | (1.56) |
| 2.72      | (0.84) |
| -0.24     | (0.17) |

Event Study Results

<table>
<thead>
<tr>
<th>Event Study Results</th>
<th>λ_{1997}</th>
<th>λ_{1999}</th>
<th>λ_{2001}</th>
<th>λ_{2006}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Year Effect</td>
<td>8.74</td>
<td>0.48</td>
<td>8.36</td>
<td>8.22</td>
</tr>
<tr>
<td></td>
<td>(4.28)</td>
<td>(0.42)</td>
<td>(4.11)</td>
<td>(3.51)</td>
</tr>
<tr>
<td>3-Year Effect</td>
<td>6.75</td>
<td>0.28</td>
<td>6.60</td>
<td>6.11</td>
</tr>
<tr>
<td></td>
<td>(2.16)</td>
<td>(0.39)</td>
<td>(2.00)</td>
<td>(1.78)</td>
</tr>
<tr>
<td>5-Year Effect</td>
<td>9.11</td>
<td>0.28</td>
<td>8.67</td>
<td>8.15</td>
</tr>
<tr>
<td></td>
<td>(2.33)</td>
<td>(0.41)</td>
<td>(2.17)</td>
<td>(1.81)</td>
</tr>
<tr>
<td>10-Year Effect</td>
<td>7.89</td>
<td>0.22</td>
<td>7.43</td>
<td>6.79</td>
</tr>
<tr>
<td></td>
<td>(2.31)</td>
<td>(0.34)</td>
<td>(2.11)</td>
<td>(1.92)</td>
</tr>
</tbody>
</table>

Implied Impact

| Using In-sample Variation | 0.79 | 0.03 | 0.76 | 0.69 | 0.25 | -0.02 |
| Aggregate Impact, West Germany | 7.651 | 243 | 7.330 | 6.642 | 2.393 | -209 |
| Using Out-of-sample Variation | 5.97 | 0.19 | 5.71 | 5.18 | 1.87 | -0.16 |
| Aggregate Impact, West Germany | 57.826 | 1,838 | 55,395 | 50,198 | 18,090 | -1,581 |

Level of Outcome in 1993

| Mean | 6.44 | 5.75 | 5.85 | 5.29 | 1.80 | 0.26 |
| S.D. | 2.80 | 0.47 | 2.60 | 2.21 | 0.98 | 0.18 |

# Observations | 10,626 | 10,626 | 10,626 | 10,626 | 10,626 | 10,626 |

a “New Hires” are individuals who were not employed in a SNF in the year before each index year.

b Multiples δ_{97-08} by the 9 percentage point difference in mean exposure between counties with above and below the median level of exposure.

c Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.

d Multiples δ_{97-08} by the mean of the exposure variable across counties, E_r = 0.686.

Notes: The top panel displays the pooled coefficient δ_{97-08}, obtained from estimating the differences in differences specification in Equation 3 at the county-year level, using E_r, derived in Equation 1, as the measure of a county’s exposure to the reform. The outcome variables are demographic or labor market experience of new hires, as specified in column titles. The second panel displays λ_t coefficients of the event study in Equation 2. Coefficients were normalized to zero in year t = 1993. All specifications include county and year fixed effects. Standard errors clustered at the county-level are reported in parentheses.
B Data Appendix

B.1 Cleaning and aggregation

The primary data source for the results in this paper, unless otherwise indicated, is the Integrated Employment Biographies (IEB) database. This part of the appendix describes how the IEB data are cleaned, aggregated, and outcomes coded.35

The IEB is the universe of employment spells for the universe of workers subject to social security contributions in Germany from 1975 to 2019, consisting of all individuals in Germany who fall into one of the following five employment categories: 1) employment subject to social security (in the data since 1975), 2) marginal part-time employment (in the data since 1999), 3) benefit receipt according to the German Social Code, Book III (since 1975) or II (since 2005), 4) officially registered as job-seeking at the German Federal Employment Agency, or 5) (planned) participation in programs of active labor market policies (in the data since 2000). Start and end dates of spells are reported to day-level precision.

We subset the raw IEB data by keeping employment spells (originating in the IEB’s “Employee History (BeH)” source data set) and unemployment spells only (from the IEB’s “Benefit Recipient History [LeH]” or “Unemployment Benefit II Recipient History [LHG]” source data sets). Moreover, we drop spells with a daily wage or benefit rate equal to zero, marginal part-time employment spells (variable “employment status [erwerbstatus]” equal to 109 or 209), and spells corresponding to employment notifications due to a lump-sum payment (variable “reason of cancellation/notification/termination [grund]” equal to 154). We also drop employment spells corresponding to workplaces in East Germany, Berlin, or Bremen.

Next, we aggregate the accordingly subset IEB data to the individual-year level by selecting spells covering June 30th of a given year, dropping spells not covering June 30th, and splitting spells covering multiple instances of June 30th across more than one year, for which we use a script prepared by the IAB (Eberle and Schmucker, 2019). In the case of persisting duplicate individual-year observations, we keep the spell with the highest reported daily wage/benefit rate.

We fill gaps in individual-year-level data due to temporary absence from the labor market in the geographies that provide our data (e.g., because of temporary self-employment, maternity leave, or relocation to East Germany, Berlin, Bremen, a different country), so that our analytic data set becomes an unbalanced individual-year panel of labor market histories without gaps.

35 A comprehensive introduction to (and codebook for) a processed, representative 2% extract of the IEB data, the Sample of Integrated Labour Market Biographies (SIAB), is available at (Antoni et al., 2019).
B.2 Variable coding

We define a Skilled Nursing Facility (SNF) as an establishment with WZ73 industry codes 710, 711, and 712 for private and for-profit institutions or “homes” (710); private, not-for-profit homes (711); and homes in public ownership (712). As WZ73 had been discontinued and replaced with alternative, more granular industry classifications after 2002, we impute time-consistent WZ73 codes, following the procedure of Eberle et al. (2011).

The majority of analyses focus on “regular” SNF employees, which we define, following the IAB convention, if the variable “employment status” [erwerbstatus] takes on values 101 (“Employees subject to social security with no special features”) or 140 (“Seamen”) and 143 (“Maritime pilots”). Examples for nonregular employees are apprentices, workers in part-time pre-retirement employment, and working students.

We define an SNF hire as new in year $t$ if an individual is observably employed in an SNF in year $t$ but had not been employed in an SNF in year $t-1$. As our identification strategy exploits spatial variation in exposure to the reform, we rely on county-level workplace data, which we impute during non-employment spells with the most recent observable county of work.

The IEB reports information on income via the variable “Daily wage, daily benefit rate [tentgelt],” which, depending on the source data set, may have different interpretations. During employment observations from the BeH, the variable contains data on “the employee’s gross daily wages […] calculated from the fixed-period wages reported by the employer and the duration of the (unsplit) original notification period in calendar days” in EUR (Antoni et al., 2019). Daily wages are top-coded at the level of the upper earnings limit of the statutory pension insurance, with possible exceptions due to annual bonus payments or employment interruptions. We replace daily gross wages exceeding the upper earnings limit with the limit that applied during the respective year. For unemployment spells from the LeH, the “Daily wage, daily benefit rate” variable contains information on daily benefits, which, prior to 1998, apply to working days, and, during subsequent years, to calendar days.

Next, we construct several worker characteristics. For each individual in years 1990–2008, we construct a 15-year rolling labor market experience measure by counting the number of years the respective individual was in any kind of employment throughout the preceding 15 years. We construct an equivalent measure corresponding to the 15-year rolling SNF experience.

Moreover, we construct a dummy that is equal to 1 for individuals who passed the Abitur, the German A-levels equivalent, usually obtained after 12 or 13 years of schooling and indicated by values of the raw schooling [schule] variable equal to 8 (upper secondary school leaving certificate from a specialized upper secondary school (Fachoberschule), general upper secondary school leaving certificate, A-level equivalent,
qualification for university) or 9 (general upper secondary school leaving certificate, A-level equivalent, qualification for university). Individuals who have the Abitur dummy equal to zero accordingly have obtained less than 12 years of schooling, have failed the A-levels examination or have the raw schooling variable missing. We code a second dummy that is ”1” for individuals who have obtained a bachelor’s degree or equivalent, corresponding to values of the raw tertiary-education [ausbildung] variable of 11 (degree from a university of applied sciences) or 12 (university degree).

C Classification tree

This section describes the data and algorithm we use to estimate SNF hiring probabilities in the Labor Market Sample.

C.1 Estimation and prediction samples

We construct the estimation data set by extracting a 5% random sample of person histories from the Labor Market Sample. We oversample SNF employees by adding to the training data SNF employees from the remaining 95% of the Labor Market Sample.

We next estimate hiring probabilities for every observation in the estimation data set by computing a classification tree model, for which we use R’s rpart package and specify the “class” option. We use a set of nine predictors to obtain hiring probabilities, the coding of which is outlined in section C.2, below. Last, we use the model’s predictions to obtain hiring probabilities for all observations in the Labor Market Sample.

C.2 Five-year-lagged predictors

This section specifies the set of variables used by the CART prediction algorithm to assign SNF hiring probabilities to potential SNF employees.

1. Age.
2. Female dummy.
3. German dummy.
   
   We replace any missing values of this dummy at time $t$ with non-missing values at time $t + 1$.
4. Dummy for employment in the medical sector.
   
   We construct a dummy that takes on the value of 1 for observations in medical employment, using the WZ73 industry and the KldB1988 occupation classifications. If an individual was not yet
in the data in \( t - 5 \), or if information on industry and occupation was missing in \( t - 5 \), we replace this predictor with 0. WZ73 industry codes that we use to identify health-care employees are as follows: i) 710 Heime als Unternehmen; ii) 711 Private Heime von Organisationen; iii) 712 Heime von Gebietskoerperschaften und Sozialversicherung; iv) 780 Freiberufliches Gesundheitswesen; v) 781 Privon Krankenhaeuser, Kliniken, Sanatorien; vi) 782 Krankenhaeuser, Kliniken, Sanatorien von Organisationen; vii) 783 Krankenhäuser, Kliniken, Sanatorien von WZ73 industry codes that we use to identify health-care employees are as follows: i) 710 Heime als Unternehmen; ii) 711 Private Heime von Organisationen; iii) 712 Heime von Gebietskoerperschaften und Sozialversicherung; iv) 780 Freiberufliches Gesundheitswesen; v) 781 Privon Krankenhaeuser, Kliniken, Sanatorien; vi) 782 Krankenhaeuser, Kliniken, Sanatorien von Organisationen; vii) 783 Krankenhäuser, Kliniken, Sanatorien von Gebietskoerperschaften; viii) 784 Krankenhäuser, Kliniken, Sanatorien von Sozialversicherungstraegern; ix) 880 Organisationen der freien Wohlfahrtspflege. KldB1988 occupation classes used to identify healthcare workers are i) 841 Ärzte; ii) 842 Zahnärzte; iii) 844 Apotheker; iv) 851 Heilpraktiker; v) 852 Masseure, Krankengymnasten und verwandte Berufe; vi) 853 Krankenschwestern, -pfleger, Hebammen; vii) 854 Helfer in der Krankenpflege; viii) 855 Diätassistenten, Pharmazeutisch-technische Assistenten; ix) 856 Sprechstundenhelfer; x) 857 Medizinallaboranten; xi) 861 Sozialarbeiter, Sozialpfleger; xii) 862 Heimleiter, Sozialpädagogen.

5. Unemployment at \( t - 5 \).

The unemployment dummy takes on the value of 1 for observations with employment-status [Erwerbsstatus] variable equal to 1 (full age employable recipients of ALG II), 11 (unemployment benefits), 12 (unemployment assistance) or 13 (maintenance allowance). If an individual was not yet in the data at \( t - 5 \), or information on employment status was missing at \( t - 5 \), we replace this dummy with 0.


We construct a categorical variable that contains values of the raw schooling variable [schule]. Possible values in the IEB are 5 (Grade / lower secondary school with or without a leaving certificate, intermediate school leaving certificate, or equivalent qualification), 8 (Upper secondary school leaving certificate from a specialized upper secondary school (Fachoberschule), general upper secondary school leaving certificate, A-level equivalent, qualification for university) and 9 (General upper secondary school leaving certificate, A-level equivalent, qualification for university). If an individual was not yet in the data at \( t - 5 \), or if information on schooling was missing at \( t - 5 \), we replace this variable with 1,000. More details on the raw schooling variable may be found in Antoni et al. (2019).

7. Tertiary education.

We construct a categorical predictor that contains values of the raw tertiary education variable [ausbildung]. Possible values are 1 (No vocational training), 2 (In-company vocational training/traineeship/external vocational training), 11 (degree from a university of applied sciences) and 12 (university degree). If an individual was not yet in the data at \( t - 5 \), or if information on training was missing at \( t - 5 \), we
replace this variable with 1,000. More details on the raw tertiary education variable may be found in Antoni et al. (2019).

8. Two-digit industry classification WZ73.

We construct a categorical predictor that contains values of the time-consistent industry classification WZ73 variable aggregated to the two-digit level. If an individual was not yet in the data at $t - 5$, or if the industry variable was missing or featured a negative value at $t - 5$, we replace this predictor with 1,000.


We construct a categorical predictor that contains values of the occupation classification KldB1988 [beruf], aggregated to the two-digit level. If an individual was not yet in the data at $t - 5$, or if the occupation variable was missing or featured a negative value at $t - 5$, we replace this predictor with 1,000.

D Model Details

D.1 Equilibrium Wages and Queues

Abstracting away from clearing output markets, we here solve the simplified optimization problem:

$$\max_{w^\phi, q^\phi} u_{ij}$$

s.t. $\eta(q^\phi_j) \times (p_j \times \phi - w^\phi_j) - c \times \phi = 0$

$$w^\phi_j = \Delta w + \beta \times (p_j \times \phi) \text{ if } j \text{ is constrained by collective bargaining .}$$

Starting with labor markets that are not constrained by collective bargaining, we solve equation (15) for wages and plug this into flow utilities:

$$u_{ij} = \mu(q^\phi_j) \times (p_j \times \phi(i) - \frac{c \times \phi(i)}{\eta(q^\phi_j)} + (1 - \mu(q^\phi_j)) \times b^\phi(i) + \epsilon_{ij} .$$

Using $\eta(q) = \mu(q) \times q$, we have

$$u_{ij} = \mu(q^\phi_j) \times p_j \times \phi(i) - \frac{c \times \phi(i)}{q^\phi_j} + (1 - \mu(q^\phi_j)) \times b^\phi(i) + \epsilon_{ij} .$$

(17)
We note that
\[
\frac{\partial \mu(q_j^\phi)}{\partial q_j^\phi} = \frac{\partial \eta(q_j^\phi)}{\partial q_j^\phi} = \frac{\eta(q_j^\phi)}{(q_j^\phi)^2} \times (\epsilon - 1) \quad (18)
\]
where \( \epsilon = \frac{\phi^i q_j^\phi}{\eta(q_j^\phi)} \) is the elasticity of the matching function. Using this and maximizing equation (17) with respect to \( q_j^\phi \), we get:
\[
\frac{\partial u_{ij}}{\partial q_j^\phi(i)} = (p_j \times \phi(i) - b^\phi(i)) \times \mu(q_j^\phi(i)) \times (\epsilon - 1) + \frac{c \times \phi(i)}{(q_j^\phi(i))^2} = 0
\]

Multiplying by \( q_j^\phi(i) \) and using \( \frac{c \times \phi(i)}{q_j^\phi(i)} = \mu(q_j^\phi(i)) \times (p_j \times \phi(i) - w_j^\phi(i)) \) (from equation (15)) we can simplify to
\[
\mu(q_j^\phi(i)) \times \left( (\epsilon - 1) \times (p_j \times \phi(i) - b^\phi(i)) + (p_j \times \phi(i) - w_j^\phi(i)) \right) = 0
\]

Rearranging, we find that that equilibrium wages for firms not affected by collective bargaining are given by
\[
w_j^\phi = \epsilon \times (p_j \times \phi) + (1 - \epsilon) \times b^\phi
\]

Together, equilibrium wages are given by
\[
w_j^{\phi,*} = \begin{cases} 
\Delta w + \beta \times (p_j \times \phi) & \text{if } j \text{ is constrained by collective bargaining} \\
\epsilon \times (p_j \times \phi) + (1 - \epsilon) \times b^\phi & \text{else} 
\end{cases}
\quad (19)
\]

and equilibrium queues are determined by the free entry condition (equation (15)) evaluated at equilibrium output prices and wages.

### D.2 Details on Welfare Analysis

In this subsection, we provide details on how we arrive from the welfare equation (12) to the effects of the product subsidy on welfare summarized in equation (13).

The product subsidy affects welfare directly and through the endogenous equilibrium changes in prices and quantities. We first note that holding quantities fixed, changes in the subsidy amount, output prices, and wages denote transfers between stakeholders and do not add to welfare. Starting with output prices and the subsidy, we note that \( p_j^c = p_j - \tau_g(j) \) and that \( X_j = \sum_{\phi} s_j^\phi(w_j^\phi, q_j^\phi) \times \mu(q_j^\phi) \times \phi \). That means that the output price terms in the consumer surplus \( (p_j^c \times X_j) \) and in the producer surplus \( (s_j^\phi \times \mu(q_j^\phi) \times p_j \times \phi) \) and
the subsidy term in the government surplus \((-s_j^\phi \times \mu(q_j^\phi) \times \tau_g(j) \times \phi)\) cancel out in equation (12) as they refer to a transfer between consumers, firms, and the government.

Similarly, changes in wage, conditional on \(s_j^\phi(w, q, \phi)\), are simply transfers between the producers and workers and hence do not add to welfare:

\[
\frac{\partial W}{\partial w_j^\phi} \bigg|_{q, s} = -s_j^\phi(w, q, \phi) \times \mu(q_j^\phi) + s_j^\phi(w, q, \phi) \times \mu(q_j^\phi) = 0.
\] (20)

This allows us to focus on changes in quantities stemming from a relocation between labor markets and a relocation within labor markets that we turn to next.

**Relocation between sectors:** Changes in workers’ application decisions affect welfare as follows:

\[
\frac{\partial W}{\partial s_j^\phi} \bigg|_{q, w, s-j} = v_{X_j} \times \frac{\partial X_j}{\partial s_j^\phi} - \mu(q_j^\phi) \times w_j^\phi - \frac{c \times \phi}{q_j^\phi} - (1 - \mu(q_j^\phi)) \times UEB
\]

\[
= p_j^\phi \times \mu(q_j^\phi) \times \phi - \mu(q_j^\phi) \times w_j^\phi - \frac{c \times \phi}{q_j^\phi} - (1 - \mu(q_j^\phi)) \times UEB
\]

\[
= p_j^\phi \times \mu(q_j^\phi) \times \phi - \mu(q_j^\phi) \times p_j \times \phi - (1 - \mu(q_j^\phi)) \times UEB
\]

\[
= -\tau_g(j) \times \phi \times \mu(q_j^\phi) - (1 - \mu(q_j^\phi)) \times UEB,
\] (21)

where the third line uses the free entry entry condition. Marginal workers are indifferent between sectors, which implies that changes in application behavior only affect welfare through the traditional DWL in the product market, captured by the first term and fiscal externalities, denoted by the second term to the extent that the relocation contributes to a net reduction in unemployment.
Relocation within sectors: Next, we turn to changes in labor market queues $q_i^o$. Using equation (18), we have:

$$\frac{\partial W}{\partial q_j} \bigg|_{s,w,q_{-j}} = p_j \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times s_j^o(w^o, q^o) \times \phi \times (\epsilon - 1)$$

$$- s_j^o(w^o, q^o) \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times \epsilon - 1 + s_j^o(w^o, q^o) \times \frac{c \times \phi}{\eta(q_j^o)} \times \frac{\eta(q_j^o)}{(q_j^o)^2}$$

$$+ s_j^o(w^o, q^o) \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times (\epsilon - 1) - s_j^o(w^o, q^o) \times b^o \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times (\epsilon - 1)$$

$$+ s_j^o(w^o, q^o) \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times (\epsilon - 1) \times UEB$$

where $\epsilon = \frac{\eta(q_j^o)}{p_j}$ is the elasticity of the matching function. Next we drop the positive and negative $s_j^o(w^o, q^o) \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times (\epsilon - 1)$ term. Then we use the free entry condition and replace $\frac{c \times \phi}{\eta(q_j^o)}$ by $p_j \times \phi - w^o_j$. Finally, adding and subtracting $p_j \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times s_j^o(w^o, q^o) \times \phi \times (\epsilon - 1)$, we have:

$$\frac{\partial W}{\partial q_j} \bigg|_{s,w,q_{-j}} = -\tau_g(j) \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times s_j^o(w^o, q^o) \times \phi \times (\epsilon - 1) + s_j^o(w^o, q^o) \times \frac{\eta(q_j^o)}{(q_j^o)^2} \times (\epsilon - 1) \times UEB$$

$$+ \frac{\eta(q_j^o)}{(q_j^o)^2} \times s_j^o(w^o, q^o) \left[ p_j \times \phi \times (\epsilon - 1) + (p_j \times \phi - w^o_j) + (1 - \epsilon) \times b^o \right]$$

Simplifying the terms in brackets, we have:

$$\frac{\partial W}{\partial q_j} \bigg|_{s,w,q_{-j}} = -\tau_g(j) \times \frac{\mu(q_j^o)}{q_j^o} \times s_j^o(w^o, q^o) \times \phi \times (\epsilon - 1)$$

$$+ s_j^o(w^o, q^o) \times \frac{\mu(q_j^o)}{q_j^o} \times (\epsilon - 1) \times UEB$$

$$- \frac{\mu(q_j^o)}{q_j^o} \times s_j^o(w^o, q^o) \left[ w^o_j - (\epsilon \times p_j \times \phi + (1 - \epsilon) \times b^o) \right]$$

Equilibrium Wage - Efficient Wage

The first term contributes to the traditional DWL in the product market and the second term contributes to fiscal externalities to the extent that changes in labor market tightness affect unemployment within the sector. The last term denotes the welfare effects in the labor market, which is proportional to the wedge between the “efficient” wage (constrained only by search frictions) and the equilibrium wage. As discussed
earlier, firms in labor markets that are not affected by collective bargaining will post the efficient wage, setting the wedge to zero. In contrast, when collective bargaining frictions lift equilibrium wage beyond the efficient wage, unemployment will be inefficiently high. In this case, decreases in the labor market queue length contribute positively to social welfare through this third channel. The opposite holds true when the equilibrium wage falls below the efficient wage level.\textsuperscript{36}

**Overall Welfare Effects:** Finally we combine the partial effects across firms to characterize the overall effects of the product subsidy on social welfare. To simplify notation and interpretation, we let $m^\phi_j$ denote the population share of workers employed in (matched to) firm $j$ and let $\omega^\phi_j$ the (population) share of workers who applied to $j$ but remained unemployed. Specifically:

\[
m^\phi_j = \mu(q^\phi_j) \times s^\phi_j(w^\phi_j, q^\phi_j),
\]
\[
\omega^\phi_j = (1 - \mu(q^\phi_j)) \times s^\phi_j(w^\phi_j, q^\phi_j).
\]

Building on these terms, we can express the overall effect of the subsidy in one industry, the SNF industry, on social welfare as follows:

\[
\Delta W = \int_0^{\tau_{SNF}} \partial W / \partial \tau_{SNF} d\tau = \int_0^{\tau_{SNF}} \sum_j \sum_\phi \left( \frac{\partial W}{\partial s^\phi_j} \times \frac{\partial s^\phi_j}{\partial \tau_{SNF}} + \frac{\partial W}{\partial q^\phi_j} \times \frac{\partial q^\phi_j}{\partial \tau_{SNF}} \right) d\tau_{SNF}
\]
\[
= \int_0^{\tau_{SNF}} \sum_j \sum_\phi \left( -\tau_{g(j)} \times \phi \times \frac{\partial m^\phi_j}{\partial s^\phi_j} \times \frac{\partial s^\phi_j}{\partial \tau_{SNF}} + \frac{\partial m^\phi_j}{\partial \mu} \times \frac{\partial \mu}{\partial s^\phi_j} \times \frac{\partial m^\phi_j}{\partial \tau_{SNF}} \right) d\tau_{SNF}
\]
\[
- \left( \frac{\partial \omega^\phi_j}{\partial s^\phi_j} \times \frac{\partial s^\phi_j}{\partial \tau_{SNF}} + \frac{\partial \omega^\phi_j}{\partial \mu} \times \frac{\partial \mu}{\partial s^\phi_j} \times \frac{\partial \omega^\phi_j}{\partial \tau_{SNF}} \right) \times UEB
\]
\[
+ \left( \frac{\partial m^\phi_j}{\partial \mu} \times \frac{\partial \mu}{\partial s^\phi_j} \times \frac{\partial \omega^\phi_j}{\partial \tau_{SNF}} \right) \times \left( w^\phi_j - \epsilon \times p_j \times \phi + (1 - \epsilon) \times b^\phi \right) \right) d\tau_{SNF}.
\]

To give further intuition for the labor market surplus, it is instructive to use the free entry condition

\textsuperscript{36}For comparison, in a random search model with Nash bargaining over wages, the wedge in wages boils down to whether the Hosios (1990) condition holds, which requires that the Nash bargaining weight equals the elasticity of the matching function.
and to replace the wage, $w^φ_j$, by $p_j × φ - \frac{c×φ}{η(q^φ_j)}$. The labor market surplus can then be rewritten as

$$\text{Labor Market Surplus} = \frac{∂m^φ_j}{∂μ} × \frac{∂μ}{∂q^φ_j} × \frac{∂q^φ_j}{∂τ_{SNF}} \times \left[ p_j × φ - b^φ - \frac{c × φ}{(1 - ϵ) × η(q^φ_j)} \right]. \quad (23)$$

The extra vacancy costs capture changes in the match probability $η$, as the queue length changes, because it affects all, not just marginal, matches. This is captured by the factor $(1 - ϵ)$ in the denominator. For instance, when the the match probability is invariant to the queue length, then $ϵ = 0$ and the incremental vacancy cost per extra match are simply $\frac{c × φ}{η(q^φ_j)}$.

The match surplus equals the extra vacancy costs in equilibrium when wages are not constrained by collective bargaining. The surplus exceeds (falls) short of the incremental vacancy costs when wages are inefficiently high (low).

### D.3 Elasticity of the Matching Function

Our back-of-the-envelope calculation assumes a constant elasticity of the matching function in SNF labor markets within a skill segment. Popular and more flexible matching functions have that the matching elasticity is actually falling in the queue length. For instance, an alternative matching function discussed in Acemoglu and Shimer (1999) implies that $η(q) = 1 - exp(-q)$. The elasticity is then

$$ϵ(q) = \frac{q × exp(-q)}{1 - exp(-q)}$$

The sign of the slope of the elasticity can be expressed as $sign\left(\frac{∂ϵ(q)}{∂q}\right) = 1 - q - exp(-q)$. This function equals 0 for $q = 0$ and is strictly decreasing in $q$ for $q > 0$, which implies that the sign is negative for $q > 0$.

### D.4 Elasticity of the Matching Function and the Elasticity of Labor Supply

In this section, we draw a connection between the observed elasticity of supply and the elasticity of the matching function. We consider the case under three simplifying assumptions. First, (i) we consider only labor market, meaning that employment changes are internally driven within the labor market. (ii) We hold the elasticity of matching functions fixed and third (iii) we consider the case of constant returns to scale in the matching function.

We illustrate the connection in one skill segment and hence consider $φ = 1$ and consider firms not constrained by collective bargaining. The free entry condition simplifies to:
\[ \eta(q) \times \left[ p - \epsilon \times p - (1 - \epsilon) \times b \right] - c = 0 . \tag{24} \]

In the data, we observe the elasticity of matches w.r.t. wages \( e_{m,w} \). Under (i)-(iii), we have that

\[ e_{m,w} = \frac{\partial m}{\partial w} \times \frac{w}{m} = \frac{\partial m}{\partial p} \times \frac{p}{m} \times \frac{\partial p}{\partial w} \times \frac{w}{p} = e_{m,p} \times \frac{1}{e_{w,p}} , \tag{25} \]

where \( e_{m,p} \) is the elasticity of matches w.r.t. output price and \( e_{w,p} \) is the elasticity of the wage w.r.t. output price. This can be expressed as

\[ \frac{1}{e_{w,p}} = \frac{p - b}{p} + \frac{b}{\epsilon \times p} . \tag{26} \]

Because of (i) we have that queue length only varies in vacancies and hence

\[ e_{m,p} = e_{m,v} \times e_{v,p} = (1 - \epsilon) \times e_{v,p} , \tag{27} \]

where the second equality uses (iii). We also have

\[ e_{v,p} = -e_{q,p} = \frac{1}{\epsilon} \times \frac{p}{p - b} , \tag{28} \]

where the second equality uses the relationship between \( dq \) and \( dp \) from total differentiating the free entry condition. Combining all the terms, we have

\[ e_{m,w} = \frac{1 - \epsilon}{\epsilon} \times \frac{p}{p - b} \times \frac{1}{e_{w,p}} = \frac{1 - \epsilon}{\epsilon} \times \left( 1 + \frac{b}{\epsilon \times (p - b)} \right) . \tag{29} \]

Simplifying terms, we have

\[ e_{m,w} = \frac{1 - \epsilon}{\epsilon} \times 1 + \frac{1 - \epsilon}{\epsilon^2} \times \frac{b}{p - b} . \tag{30} \]

In the special case of \( b = 0 \) we have a monotone relationship between the observed supply elasticity and the elasticity of matching function. We have that the supply becomes perfectly elastic as \( \epsilon \) converges to 0. For \( b > 0 \), the supply elasticity further increase in \( b/(p - b) \). Holding output prices fixed, the scaling factor increases in UI benefits that raise \( b \), particularly so for lower skilled workers where the denominator (adding skills back in), \( p \times \phi - b \) is smaller.