General Equilibrium Effects of Insurance Expansions: Evidence from Long-Term Care Labor Markets*

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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 show conceptually that, in the spirit of Harberger (1971), in a second-best equilibrium in which 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.

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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).[1] 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 (2012) 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 role of healthcare jobs in the broader economy (Baicker and Chandra, 2012) 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 Pflege[3] (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 churches (Diakonie) 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.[7] These agreements typically result in wage compression and wages that significantly exceed market

[2]See, 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).

[3]Help for Care.

[4]According to Rothgang (1997), p. 44, inpatient care providers were assured that their costs of care provision would be reimbursed from state and municipal budgets.

[5]See Table 4 in Rothgang (1997).

[6]See § 93 Bundessozialhilfegesetz (BSHG) 1992.

[7]Survey data from 2011 suggest that 80.6% of public and not-for-profit SNF providers set wages via collective bargaining agreements. See `shorturl.at/zAB26`, accessed September 7, 2021.

wages, particularly so for lower-skilled workers.[8] In Section 5, we will come back to the role of 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.[9]

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. [10]

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 2A). Coverage rollout has led to a dramatic growth of the LTC sector in Germany, according to contemporary market observers and government reports (Bundesministerium für Arbeit und Soziales, 1997; Rothgang, 1997) alike.[11]

[8]Estimates from Bispinck et al. (2013) suggest that employees in nursing- related occupations earn 20% less if their wages are not set through collective bargaining agreements.

[9]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.

[10]In 1999, market prices for patients with the highest but also the most common care needs equaled 65 EUR per patient per day for health care 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.

[11]The diminished importance of HzP as a revenue source has also led to a leveling in the playing field between

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.[12] IEB is the universe of employment spells for the universe of workers subject to social security contributions in Germany from 1975 to 2019.[13] 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.[14] 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)[15] at least once[16] 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

private, public, and not-for-profit providers.

[12] 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.

[13] 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).

[14] We first clean the spell-level observations following (Eberle and Schmucker, 2019).

[15] 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).

[16] We only consider "regular" employment following the IAB convention—see Appendix B.2 for details.

observations from year 1980 onward. We stop the sample in year 2004 because of changes in the 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 (due to missing data). These data are available from 1991 to 2017 (Statistische Ämter des Bundes und der Länder, 2021).[17] The second source is the Human Mortality Database, which allows us to compute age-by-sex mortality for years 1991–2008 for former West Germany and 28 other countries.

[17] Mortality 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*).[18]

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).[19]

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)[20]. Some 61% of observations are for employment in the health-care 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,

[18] Counts of recipients of Hilfe zur Pflege at the state level were obtained from Statistisches Bundesamt (1993, Page 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).

[19] 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.

[20] 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 4 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 health-care 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.[21] 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

[21] 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:

$$E_r = 100\% - \frac{HzP_{r,1993}}{g_{r,1993,1999} * LTCClaims_{r,1999}}, \tag{1}$$

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 1999 to that in 1993. 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:

$$Y_{c(r)t} = \alpha_c \times \mathbf{1}(\text{county}_c) + \delta_t \times \mathbf{1}(\text{year}_t) + \sum_{t=1975}^{t=2008} \lambda_t \times (E_r) \times \mathbf{1}(\text{year}_t) + \epsilon_{c(r)t} \tag{2}$$

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:

$$
\begin{aligned}
Y_{ct} = \alpha_c \times \mathbf{1}(\text{county}_c) + \delta_t \times \mathbf{1}(\text{year}_t) + \sum_{t=1975}^{t=1992} \delta_t \times (E_r) \times \mathbf{1}(\text{year}_t) \\
+ \delta_{94-96} \times (E_r) \times \mathbf{1}(\text{year}_{94-96}) \\
+ \delta_{97-08} \times (E_r) \times \mathbf{1}(\text{year}_{97-08}) + \epsilon_{ct}
\end{aligned}
\tag{3}
$$

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 of 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[22]), 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.[23] 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 aged 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 2 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

[22] As in our primary analysis, we use the WZ73 industry classification system.

[23] 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 3, 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 3) per capita across all counties in 1993. In the post–insurance rollout years, shaded in grey, the number of establishments and 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 3, 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 (A) and (B) 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 many 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 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 prereform employment (32 workers) and postreform employment (32+30.5)—see column 2 in Table 2. The denominator considers the change in prices. Prereform, 68.6% of potential patients paid the full price out-of-pocket, the remaining 31.4% were fully insured through means-tested HzP. So the average out-of-pocket price was $0.686P_{market}$. Postreform, the cost-sharing of the newly insured drops to 43%. The new average out-of-pocket price then becomes $0.686 * 0.43P_{market}$. The effective change in the average price is then 68.6%*(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.3 and Table A1), with other ways of constructing the exposure measure (Figures A.4 and A.5, Table A2, and with controls for geographic trends in aging (Figure A.6 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.[24] 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

[24] 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.[25] As a result, the sample share of individuals employed in inpatient LTC in period t increases 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 a 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 three

[25] We maintain $\frac{0.0265 \cdot 5{,}912{,}810}{0.0056 \cdot 48{,}106{,}142}$=58.2% of the workers employed in SNF in period t.

important differences between the specifications here and 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 conclusive 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 employment 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 a 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 4 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 4 and column (1) in Table 5) as well as the synthetic control method and mortality data from other countries (Panel B in Figure 4 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 4 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

Our empirical findings imply that the expansion of LTC insurance coverage, which introduced a fixed-price subsidy for LTC services, resulted in more workers and firms moving into the SNF sector. Wage adjustments were close to zero for both the incumbent workers and the new hires, but the skill composition of the new hires changed. The expansion brought predominantly lower-skilled workers into SNF employment. A substantial share of these workers would have been unemployed in the absence of coverage expansion. To interpret our empirical findings, we next sketch out a conceptual framework that introduces wage compression due to collective bargaining as an important feature of the SNF labor market equilibrium. Building on the conceptual discussion, we then provide a back-of-the-envelope calculation of welfare gains (on the labor market) from insurance expansion.

5.1 Frictions in the Labor Market

Our empirical finding that firms were able to hire more workers without increasing wages is consistent with two models of the labor market. One is a model of the labor market without frictions and a perfectly elastic labor supply. The other is a model with a binding wage floor generating excess labor supply. In both models, firms can hire more workers without raising the wage.

Two facts point to the model with the wage floor as the one that characterizes the SNF labor market that we study. First, empirically, we find that firms go down in the skill distribution when hiring additional workers. This is inconsistent with the existence of a perfectly elastic supply of the same skilled workers at the going wage. Second, institutionally, collective bargaining, which often leads to wage compression and an implicit wage floor for lower-skilled workers, has played an important role in SNF markets.

Until the mid-1990s, collective bargaining over wage contracts has been pervasive throughout the German labor market (Antonczyk et al., 2010; Dustmann et al., 2014). The long-term care sector is no exception. Prior to the LTC reform that we study, SNFs were predominantly in public or not-for-profit (commonly church-run) ownership, with a history of collective bargaining *across sectors* (i.e., not SNF-specific) that persists today.[26]. Collective bargaining compresses the wage distribution by compressing the distribution of workers' characteristics and the returns to productivity-relevant characteristics (Card, 1996, 2001; Card et al., 2003). Faced with limited ability to offer different wages by skill, employers try to cream-skim higher-skilled workers. The wage compression results in an implicit wage floor for lower-skilled workers, and those lower-skilled workers who do get the job enjoy the highest rents relative to their reservation wages (Card, 1996).

The price distortions in inputs—in this case, in labor—reduce efficiency of production and increase the marginal cost of a unit of care for firms. This in turn increases their prices on the product market and results in inefficiently low output.[27] As we discussed in Section 2, historical evidence suggests that as a result, SNF care was predominantly consumed by individuals eligible for means-tested HzP subsidies. Consumers not eligible for means-tested subsidizes effectively had

[26] See, e.g., https://www.ekir.de/www/downloads-archiv/bat-kf850.pdf

[27] In practice, the price on the market for long-term care was determined through bargaining between providers and public payers, both before and after the insurance expansion. The bargaining aimed to set the price of care "at cost," which allowed firms to cover higher wages.

willingness to pay for long-term care that was below market prices.

5.2 Collective Bargaining, Wage Compression and Lower-Skill Employment

We schematically illustrate the labor market equilibria in Figure 1. We assume that that firms are price-takers in the output market for care and that wages are determined through an exogenous collective bargaining agreement and are invariant across skill groups. The collective bargaining wage is denoted by w on the vertical axis.

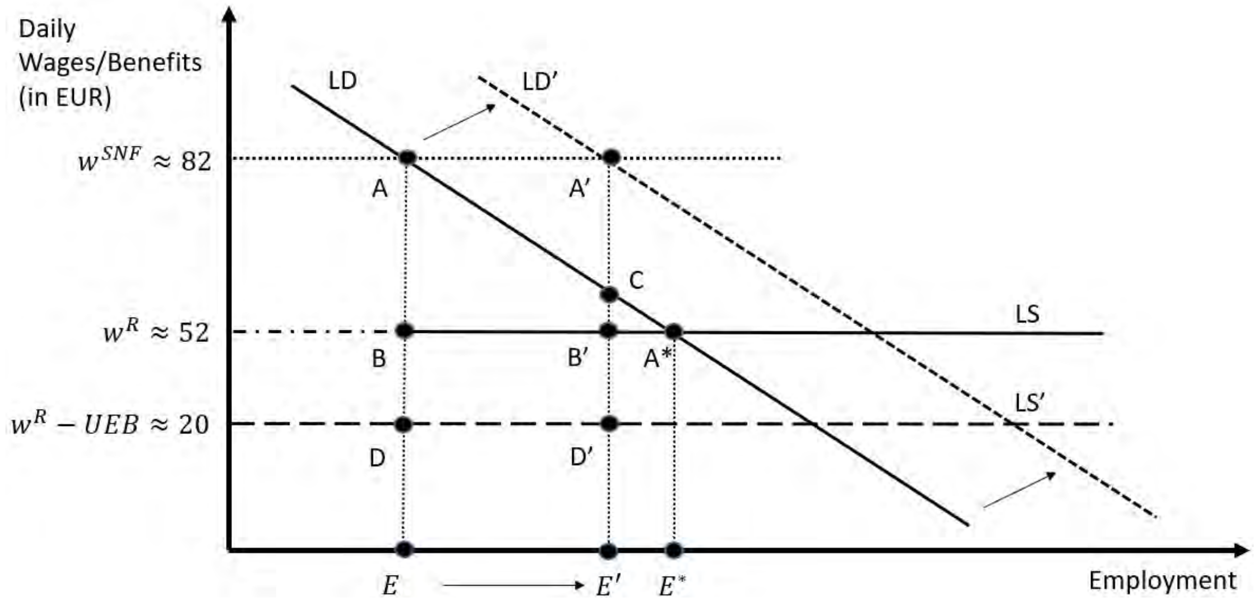
We also assume that there are two types of workers on the market: 1) higher-skilled workers with an upward sloping labor supply and 2) lower-skilled workers with lower reservation wages—who are, however, bounded from below by the level of unemployment benefits. The supply of lower-skilled workers is perfectly elastic.[28] Given w, firms cream-skim all higher-skilled workers with reservation wages at or below w and meet the residual demand for care with lower-skilled workers. To simplify the exposition, we abstract away from the (fixed) employment of higher-skilled workers and instead focus on the labor demand and supply of lower-skilled workers in Figure 1. "LD" denotes the pre-expansion labor demand curve for lower-skilled workers. At wage w, patients, and hence SNF firms, are only willing to hire E lower-skilled workers.

LS denotes the labor supply curve for lower-skilled workers. w^R denotes the reservation wage on the vertical axis. The wage floor, induced by collective bargaining, distorts equilibrium employment downward. Removing the wage floor would increase employment to E^*, given by the intersection of labor demand and labor supply. The wage floor creates a wedge between the going wage and the reservation wage, equal to the difference between points A and B. The difference generates rents that are accrued by E, employed lower-skilled workers.

We now consider the LTC reform, which introduces a subsidy in the market for SNF care. This shifts out patient demand for SNF care and, as a result, the demand for SNF workers. The new demand curve is denoted by LD'. Wages restricted by collective bargaining remain unchanged, as our empirical estimates suggest, but employment of lower-skilled workers increases from E to E'.

[28] Our qualitative insights are robust to allowing for an upward-sloping labor supply for lower-skilled workers.

Figure 1: **SNF Labor Market Equilibrium for Lower-Skilled Workers**



5.3 Welfare

5.3.1 Defining surplus

Building on this stylized model of the SNF labor market with collective bargaining and wage compression, we next attempt to quantify the welfare effects of the LTC insurance expansion. We extend the traditional welfare loss calculation from moral hazard by considering the welfare consequences in the labor market. The change in surplus from the LTC insurance expansion, taking into account the cost of government financing, then comprises the following terms, which we detail below:

$$\begin{aligned}\Delta Surplus \quad = \quad & \underbrace{-\frac{1}{2}\cdot \bar{s}\cdot \Delta E^{SNF}}_{\text{Traditional Moral Hazard}} + \underbrace{(MPL^{SNF} - w^{r,SNF})\cdot \Delta E^{SNF}}_{\text{Labor Market Surplus Change in SNF}} \\ + \quad & \underbrace{\sum_{j\neq SNF} D_j \cdot \Delta E^j}_{\text{Labor Market Surplus Change in Other Sectors}} - \underbrace{UEB\cdot \Delta UE}_{\text{Unemployment}} - \underbrace{\phi \Delta G}_{\text{Cost of Funding}} \quad . \end{aligned} \tag{4}$$

The first term denotes traditional moral hazard, which corresponds to the triangle AA'C above the old LD curve (recall that the LD curve reflects the marginal product of labor and the willingness to pay by the patients). The effect entails the welfare effect of the subsidy on consumer surplus, net of public spending. In the post-expansion equilibrium, patients consume more care and hire more workers because of the price subsidy, but their valuation of care is lower than the going wage. Following Harberger (1971), we refer to AA'C as the deadweight loss in the product market from the price subsidy $s = \bar{s}$. Specifically, $AA'C = \int_{s=0}^{\bar{s}} s \cdot \frac{\partial E^{SNF}}{\partial s} ds = \frac{1}{2} \cdot \bar{s} \cdot \Delta E^{SNF}$.

Moving workers into SNF firms may, in addition, induce a change in worker surplus in SNFs and other sectors of the economy. To incorporate the general equilibrium aspects of the price subsidy on the labor market, we need to add $\sum_j \int_{s=0}^{\bar{s}} D_j \cdot \frac{\partial E^j}{\partial s} ds = \sum_j D_j \cdot \Delta E^j$ to the surplus calculation, where D_j denotes distortions in sector j and ΔE^j denotes changes in employment. Following our stylized discussion, we assume that there is no change in surplus for higher-skilled workers and instead focus on the welfare effects for lower-skilled workers.

The second term considers the welfare effects in the SNF labor market. As we discussed above, wage compression under collective bargaining creates a wedge between the marginal product of labor, MPL^{SNF}, and the reservation wage $w^{r,SNF}$, which we capture by $D_{SNF} = MPL^{SNF} - w^{r,SNF}$. The total change in worker surplus (driven by the new hires) in the SNF market is thus given by the product of this distortion and the change in employment, which corresponds to the area AA'B'B in Figure 1.

The third term considers the implied change in labor market surplus in other sectors of the economy as workers move into SNF firms. The distortions D_j in other sectors may encompass wage frictions or firm market power in input or output markets. For example, if the price subsidy encourages workers from other sectors to switch toward SNF employment and firms cannot replace these workers on net, then the third effect will be negative if D_j is positive, as, for example, in the case of monopsony power, or positive if D_j is negative, as in the case of a production subsidy in sector j.

The fourth term in Equation 4 considers nonproductive unemployment. We set the productivity of unemployment to 0 and the wage to the collected unemployment benefits, UEB. This allows us to express the surplus contribution of unemployment as the negative of benefits scaled by changes in unemployment. We graphically capture the latter through a second labor supply curve, LS', in

Figure 1, which shifts the former curve LS downward by the unemployment benefit amount UEB. The difference between the labor supply curves LS and LS' can be interpreted as the difference between the private cost of SNF employment to workers, and the social cost of employment. If all new hires were otherwise unemployed, the gross gain in social surplus in the labor market increases to AA'D'D.

Finally, the last term in Equation 4 denotes the distortionary cost of funding the LTC price subsidies that is proportional to the extra funding ΔG and depends on the cost of public funds, ϕ. The LTC reform was funded through mandatory payroll contributions earmarked for LTC insurance, which may be costly to raise and may also have distorted employment in the broader economy.

We note that our calculation of the change in welfare is incomplete, as we do not consider the welfare effects on other factors of production or the broader effects on consumption. These changes would need to be accounted for if these markets are also distorted and the quantity of traded units is affected by the LTC price subsidies. As discussed earlier, this may increase or reduce the overall welfare effects depending on the sign of the distortion and the sign of the change in traded units.

5.3.2 Measurement

We now provide a back-of-the envelope quantification of the theoretical object in 4 in our empirical setting.

SNF employment and wages: We start with the second term and focus on the workers whom we characterized as being in the SNF hiring pool in Section 3.2. Concretely, we consider the sample of workers in year 1993 for whom we predicted a more than 1% chance of being hired in an SNF. We assume that observed wages equal the marginal product of labor and assign the average daily wage in SNF employment in this sample of workers—which equals 82.35 EUR—to be the wage floor. We thus have $MPL^{SNF} = w^{SNF} \approx 82$ EUR. Measuring the reservation wage is canonically challenging, as it is not directly observed. We assume that the median of the 1993 wage distribution earned in our sample of potential SNF hires who were unemployed in the year prior to starting employment in an SNF characterizes the reservation wage and assume that no one would accept a wage below that. We therefore truncate the estimated wage distribution at 82.51 EUR, the median daily wage of SNF hires coming from unemployment, and estimate the conditional mean, which equals $w^{r,SNF} = E[w|w < w^{SNF}, UE_{t-1}] \approx$52 EUR. This points to a substantial wedge between the going wage and the reservation wage of $82 - 52 = 30$ EUR (see Mui and Schoefer (2021) for the discussion of the properties of this approach). We scale the wedge by 365 days and by employment gains. We consider two potential measures of employment gains, providing a lower bound and an upper bound on the labor market surplus from the employment expansion. We start with the flow estimates from Section 4.3 to provide a lower bound. Our findings in Section 4.3 suggest that at least 6,200 workers were newly hired out of unemployment into SNF in response to a 9 percentage point increase in LTC insurance. On the other hand, the five-year estimates on the overall employment gains suggest an expansion of 37,600 thousand workers.

Other sectors and unemployment: Turning to other sectors, the third factor in Equation 4, we find no evidence for employment changes in other sectors and assume that $\Delta E^j = 0$. In contrast, we find evidence that the increase in SNF employment can be accounted for by a decrease in unemployment and hence assume that $\Delta UE = -\Delta E^{SNF}$. We find an average unemployment benefit payment in our "at risk" sample of UEB=32.51 EUR, the fourth factor in Equation 4.

Traditional Moral Hazard: Now we return the first factor of Equation 4. To quantify the relevant subsidy, we consider the effective price distortion introduced by insurance. Around the reform period, market prices for patients with the highest, but also most common, care needs (in nursing-home care) equaled 65 EUR per patient per day for healthcare services and another 18 EUR per patient per day for room and board in 1999.[29] New 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 implies an out-of-pocket cost of about 65 + 18 − 47 = 36 EUR per patient per day, which, in turn, corresponds to 43% of the market price. Scaling this by the share not paid by consumers, 100% − 43% = 57%, with the going wage for

[29]See Durchschnittliche Vergütung für vollstationaere Dauerpflege in Pflegeheimen (pro Person und Tag in Euro). Gliederungsmerkmale: Jahre, Region, Pflegeklasse/Unterkunft und Verpflegung, reported by Gesundheitberichtserstatung des Bundes - Gemeinsam getragen von RKI und DESTATIS.

lower-skilled workers, we estimate an implicit subsidy for lower-skilled employment of $\bar{s} = 0.57 \cdot 56$ EUR $= 31.9$ EUR.

Costs of Public Funds: Finally, we consider the distortionary costs of public funding. The evidence from Figure 2A points to an additional 10 billion EUR annually in public LTC expenditures. This amount was used to increase the national LTC insurance coverage rate by 68.6 percentage points. This suggests that the government spent 10 / 68.8 $\cdot 9 = 1.3 billion EUR for the 9 percentage points of insuranc$
$sample variation in coverage. Inpatient long term care accounts for about 50\% of public insurance spending$[30]$, reducing$
$1.3 = 650 million EUR. Common estimates of the deadweight loss of taxation (in the United States) cluster around 30\%$
$650 million EUR = 195 million EUR as the cost of funding LTC insurance. At the same time, the government saves the$
which equals 15 million EUR for the in-sample variation in employment change and 91 million EUR for the overall employment gain.

Combining these elements, we can bound the overall annual welfare gain in our "at risk" population from below and above by

$$\Delta Surplus \geq -1/2 \cdot 0.57 \cdot 82 \cdot 6,200 \cdot 365 + (82 - 52 + 33) \cdot 6,200 \cdot 365 - 180\text{m} = -90.3 \text{ million EUR}$$

$$\Delta Surplus \leq -1/2 \cdot 0.57 \cdot 82 \cdot 37,600 \cdot 365 + (82 - 52 + 33) \cdot 37,600 \cdot 365 - 104\text{m} = 440.0 \text{ million EUR}$$

Ignoring the cost of public funds, the gains in the labor market exceed the traditional deadweight loss triangle by 9,505 EUR per worker per year. This is a large gain relative to the average annual income of 20,440 EUR among SNF workers. Scaled by the change in employment, the net benefits may almost equalize the cost of public funding when considering the upper bound.

5.4 Discussion

Our findings relate to a broader literature on the normative implications of insurance expansions. As noted by Baicker and Chandra (2012) and Skinner and Chandra (2018), increases in health care employment per se may be wasteful if they do not lead to improvements in patient health. LTC employment may be an outlier in this regard, given the critical importance of health care workers

[30] Die Finanzentwicklung der sozialen Pflegeversicherung, 1995–2020, Bundesgesundheitsministerium

in delivering the labor-intensive care. The existing literature points to large benefits to patients from incremental nurse employment in nursing homes (see Hackmann (2019) and Friedrich and Hackmann (2017) for evidence on U.S. and Danish nursing homes, respectively). Consistent with that, our findings from Table 5, although noisy, point to a decrease in patient mortality. We also note that our employment increases are accompanied by substantial increases in the number of establishments, suggesting improved access to care for many elderly patients.

Returning to our conceptual framework, the benefits of expansion to the patient—through increased quality and access to care—are captured in the labor demand curve. Interpreted through the lenses of the model, the employment expansion is then welfare enhancing if the marginal patients value the incremental services provided by the new hires at or above the reservation wages of the hires, net of the unemployment benefits.

Our findings point to a large wedge between the going wage and the social cost of employment, which comprises only (52-32) / 82 = 25% of the wage. If marginal workers were the only input that adjusted in response to insurance expansion, then to a first-order approximation, the expansion would increase welfare overall if the output of additional workers were valued at just 25% of their going wage.

We contrast this ratio to the potential price distortion introduced by insurance. As discussed earlier, estimates from the literature suggest that patients pay about 43% of the market price out-of-pocket. More recent estimates suggest an even larger cost-sharing rate of 54%, as discussed in Section 2. These estimates suggest that marginal patients value care at about 43 cents on the euro. In contrast, it costs society only 25 cents to produce 1 EUR of care.

This simplified cost-benefit comparison abstracts from several important considerations. First, this comparison abstracts from any behavioral frictions in the market for SNF care, which may introduce important wedges between revealed preferences and the actual care needs of the focal patient population (Baicker et al., 2015). This may bias the insights from this calculation in either direction. Second, this comparison abstracts from other inputs to production that may change in response to insurance expansion and are either substitutes or complements to lower-skilled workers. This may again bias our conclusion in either direction.

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.

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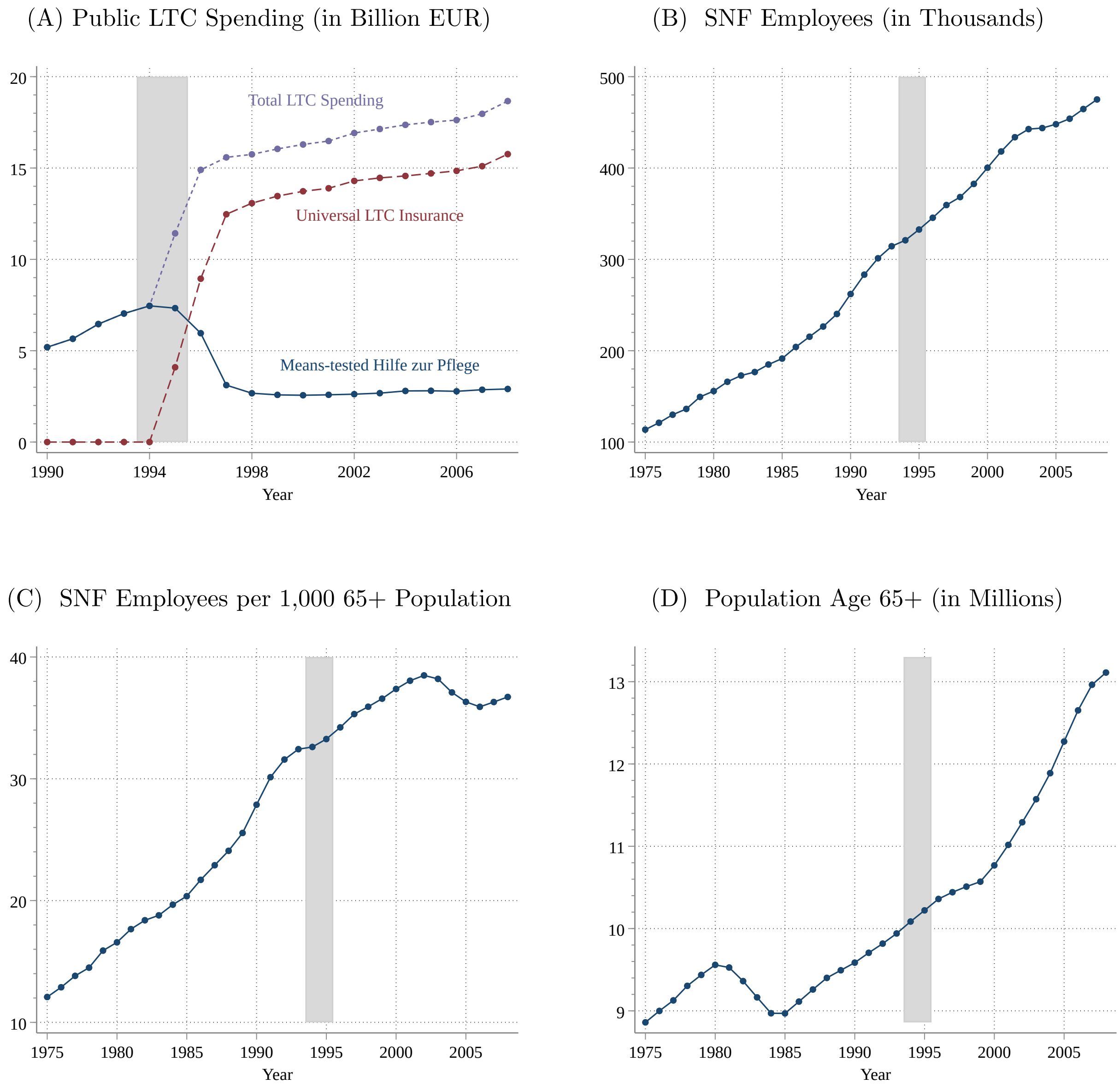
Figure 2: LTC Spending, SNF Workers, and Aging Over Time[a]

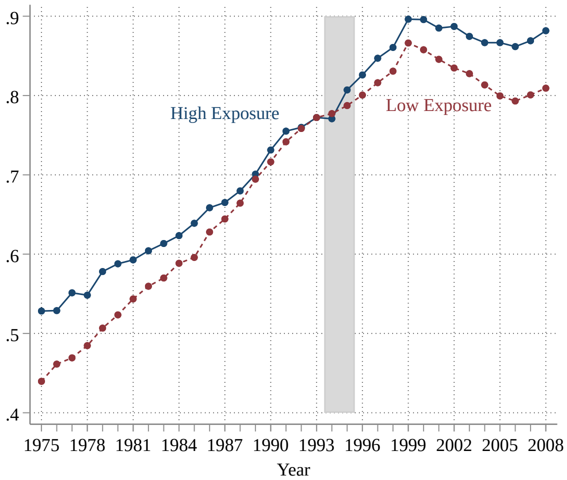


Notes: Panel A displays the evolution of the *total* public spending on long-term care benefits in Germany from 1990 to 2008, and separately by means-tested benefits (Hilfe zur Pflege) and universal long-term care insurance. Universal LTC insurance started covering outpatient services in 1995 and inpatient 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 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.

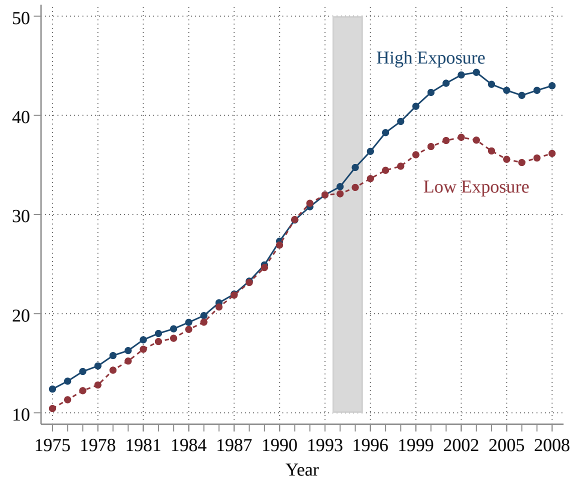
[a]LTC=Long-Term Care; SNF=Skilled Nursing Facility (inpatient LTC).

Figure 3: Introduction of Universal LTC Insurance and Supply of SNF Care

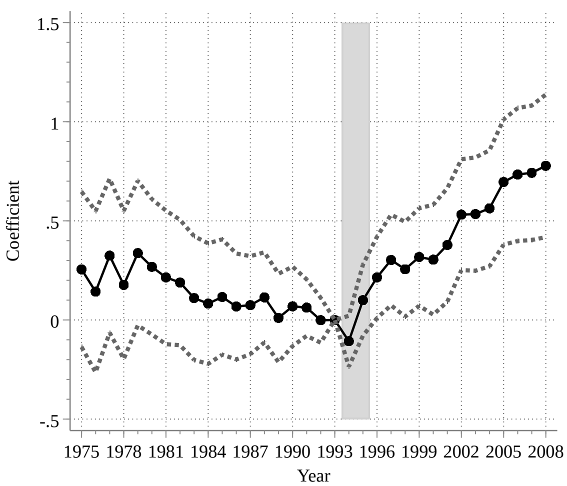
(A) SNF Firms per 1,000 65+ Population



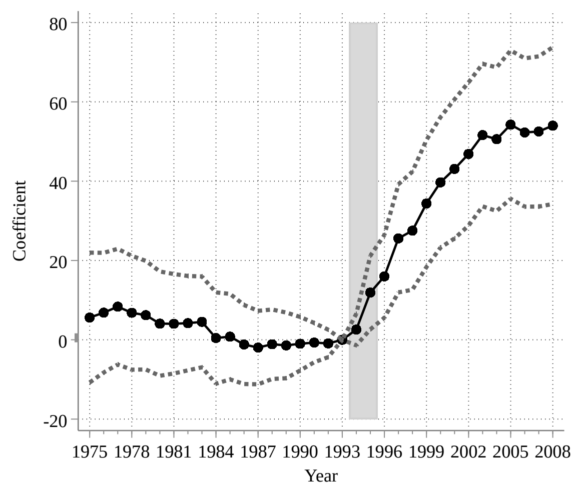
(B) SNF Workers per 1,000 65+ Population



(C) SNF Firms, Event Study

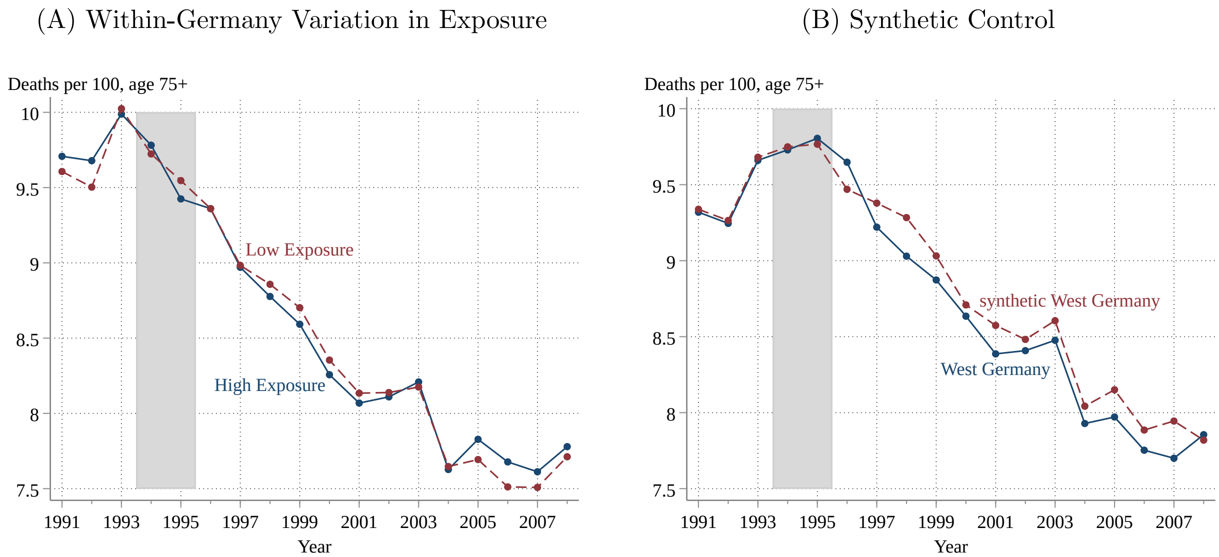


(D) SNF Workers, Event Study



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 λ_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 λ_t were normalized to zero in the pre-reform year $t = 1993$. λ_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 4: Old-Age Mortality



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.

Table 1: Summary Statistics

	SNF Sample[a]		Labor Market Sample
	All Spells	SNF Spells	All Spells
	1975-08	1975-08	1980-04
	(1)	(2)	(3)
No. of Individual-Year Observations	24,369,708	9,834,229	48,102,814
Individuals			
No. of Unique Individuals	1,589,014	1,589,014	3,818,780
Demographics			
Mean Age	37.7	41.0	41.1
% Female	77.3	80.6	41.3
% German	93.5	93.7	92.0
% High School Education (Abitur)	10.3	9.3	10.5
% in Healthcare Sector	61.0	100.0	6.3
% Unemployed	9.6	0.0	6.7
Mean 15-Year Labor Market Experience (yrs)	8.4	8.8	10.2
Mean 15-Year SNF Experience (yrs)	3.6	6.0	0.0
% Part-Time[b]	27.3	32.7	13.0
Mean Daily Wage (EUR)[c]			
All Observations	77.5	82.9	105.4
SNF Observations	82.9	82.9	80.1
Establishments			
No. of Unique Establishments			
Any	953,497	18,675	1,532,794
SNF	18,675	18,675	13,089
Of SNF Employment Spells, % in			
% For-Profit SNF		26.9	29.8
% Church-Owned SNF		58.9	56.2
% Publicly-Owned SNF		14.2	13.9

[a] SNF=Skilled Nursing Facility (inpatient long-term care)
[b] Conditional on being employed.
[c] 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

	Outcome (per 1,000 Age 65+ Population)			
	Firms	Workers	Full-time	Part-time
	(1)	(2)	(3)	(4)
Pooled Coefficients				
δ_{97-08}	0.51	44.37	21.89	22.48
	(0.13)	(8.41)	(4.95)	(4.91)
Event Study Coefficients				
1-Year Effect, λ_{1997}	0.30	25.58	13.36	12.23
	(0.12)	(6.93)	(4.34)	(3.29)
3-Year Effect, λ_{1999}	0.32	34.37	19.59	14.78
	(0.13)	(8.14)	(4.91)	(4.18)
5-Year Effect, λ_{2001}	0.38	43.10	24.98	18.12
	(0.15)	(8.92)	(5.44)	(4.82)
10-Year Effect, λ_{2006}	0.73	52.28	21.70	30.58
	(0.17)	(9.50)	(5.64)	(6.20)
Implied Impact				
Using In-sample Variation[a]	0.05	4.03	1.99	2.04
Aggregate Impact, West Germany[b]	450	39,058	19,268	19,789
Using Out-of-sample Variation[c]	0.35	30.45	15.02	15.43
Aggregate Impact, West Germany[b]	3,402	295,192	145,627	149,565
Level of Outcome in 1993				
Mean	0.77	31.98	23.11	8.87
S.D	0.34	13.58	10.11	4.52
No. of Observations	10,948	10,948	10,948	10,948

[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] Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.
[c] Multiplies δ_{97-08} by the mean of the exposure variable across counties, $\mathrm{E}_r = 0.686$.

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 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 λ_t coefficients of the event study in Equation 2. Coefficients were normalized to zero in year $t = 1993$. The results are visualized in Figure 3. 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

Outcome	Log Daily Full-Time SNF Wage			
	New Hires[a]		Incumbents[b]	
	(1)	(2)	(3)	(4)
Pooled Coefficients				
δ_{97-08}	-0.08	-0.02	-0.02	-0.01
	(0.08)	(0.01)	(0.05)	(0.04)
Event Study Results				
1-Year Effect, λ_{1997}	-0.05	-0.04	0.00	0.01
	(0.10)	(0.01)	(0.03)	(0.03)
3-Year Effect, λ_{1999}	-0.06	-0.01	-0.02	0.01
	(0.11)	(0.01)	(0.05)	(0.04)
5-Year Effect, λ_{2001}	-0.09	-0.03	-0.03	-0.01
	(0.10)	(0.01)	(0.05)	(0.04)
8-Year Effect, λ_{2004}	-0.18	-0.02	-0.03	-0.03
	(0.16)	(0.02)	(0.06)	(0.05)
Controls[c]				
15-Year LM & SNF Experience		✓		
Individual Fixed Effects				✓
Wage Level in 1993 (EUR)				
Mean	80.14	80.14	93.23	93.23
S.D.	8.18	8.18	7.05	7.05
No. of Observations	4,830	4,830	10,948	10,948

[a] "New Hires" are individuals who were not employed in a SNF in the year before each index year.
[b] SNF "Incumbents" are SNF employees who are not new hires.
[c] 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 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. The outcome variable in all columns is log of daily wage in constant 2020 Euros. 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.

Table 4: Event Study Results: Characteristics of New SNF Hires

	Outcome (Among New SNF Hires[a])							
	Age (1)	Share German (2)	Share Female (3)	Share Abitur (4)	15-Year LM Exp[b] (5)	15-Year SNF Exp[b] (6)	In Health-care in t-1 (7)	Unemployed in t-1[c] (8)
Pooled Coefficients								
δ_{97-08}	-1.03	0.04	0.04	-0.11	-3.51	-0.40	-0.09	0.14
	(1.63)	(0.04)	(0.05)	(0.04)	(0.76)	(0.37)	(0.07)	(0.06)
Event Study Results								
1-Year Effect, λ_{1997}	-1.15	0.02	0.14	-0.01	-2.67	-0.92	-0.09	0.27
	(2.00)	(0.04)	(0.06)	(0.05)	(1.05)	(0.47)	(0.12)	(0.07)
3-Year Effect, λ_{1999}	-0.97	0.06	0.05	-0.04	-2.25	-0.63	-0.09	0.11
	(1.73)	(0.04)	(0.06)	(0.05)	(0.90)	(0.47)	(0.09)	(0.07)
5-Year Effect, λ_{2001}	-1.97	0.03	0.05	-0.04	-3.79	-0.96	-0.12	0.07
	(1.83)	(0.04)	(0.06)	(0.04)	(0.94)	(0.42)	(0.08)	(0.07)
8-Year Effect, λ_{2004}	0.67	0.04	0.03	-0.12	-2.88	-0.19	-0.04	0.12
	(2.41)	(0.04)	(0.08)	(0.05)	(0.99)	(0.55)	(0.11)	(0.08)
Implied Impact								
Using In-sample Variation [d]	-0.09	0.00	0.00	-0.01	-0.32	-0.04	-0.01	0.01
Using Out-of-sample Variation[e]	-906.19	34.33	38.86	-94.90	-3088.14	-352.23	-82.77	120.34
Pre-Level								
Mean	35.48	0.91	0.83	0.09	4.73	0.94	0.15	0.18
S.D.	1.60	0.08	0.07	0.05	0.84	0.38	0.06	0.07
No. of Observations	10,620	10,620	10,620	10,620	6,118	6,118	10,620	9,332

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

Table 5: Event Study Results: Old-Age Mortality

	Outcome: Deaths per 100 in 75+ population	
	Variation in E_r	Synthetic Control
	(1)	(2)
Pooled Coefficients		
δ_{97-08}	-0.10	-0.14
	(0.75)	[p-value=0.39]
Event Study Results		
1-Year Effect, λ_{1997}	0.08	-0.16
	(0.69)	[p-value=0.25]
3-Year Effect, λ_{1999}	-0.86	-0.16
	(0.78)	[p-value=0.36]
5-Year Effect, λ_{2001}	-0.81	-0.19
	(0.89)	[p-value=0.36]
Implied Impact		
Using In-sample Variation[a]	-0.01	-
Aggregate Impact, West Germany[b]	-318	-
Using Out-of-sample Variation[c]	-0.07	-0.10
Aggregate Impact, West Germany[b]	-2,425	-4,118
Level of Outcome in 1993		
Mean[d]	10.01	9.66
S.D.	0.88	-
No. of Observations	5,238	522

[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] 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 δ_{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. λ_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 brakets 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

Predicted Hiring Risk	Risk $\geq$ 0% (1)	Risk $\geq$ 0.25% (2)	Risk $\geq$ 0.5% (3)	Risk $\geq$ 0.75% (4)	Risk $\geq$ 1% (5)	SNF in t & Risk $\geq$ 1% (6)
5-Year-Lagged Predictors						
Age (in year t-5)	36.13	34.36	34.45	33.39	33.29	34.18
% Female (in year t-5)	41.26	67.13	96.65	95.38	95.22	93.33
% German (in year t-5)	87.94	79.93	82.02	94.96	94.77	95.85
% University Education (in year t-5)	0.04	0.03	0.02	0.02	0.02	0.03
% High School Equivalent (in year t-5)	0.07	0.04	0.04	0.04	0.03	0.04
% Employed in Medical Sector (in year t-5)	5.72	15.02	21.17	30.29	17.20	24.83
% Unemployed (in year t-5)	4.30	11.98	7.03	11.60	14.06	17.70
Outcome						
% Employed in SNF (in year t)	0.56	1.32	1.70	2.39	2.66	100
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 $\geq 1\%$)

	Outcome			
	Regular Employment in			
	SNF	Hospitals	Other Healthcare	Unemployment
	(1)	(2)	(3)	(4)
Pooled Coefficients				
δ_{97-04}	0.026	-0.004	-0.014	-0.053
	(0.013)	(0.020)	(0.015)	(0.017)
Event Study Results				
1-Year Effect, λ_{1997}	0.010	0.009	-0.018	0.019
	(0.015)	(0.019)	(0.015)	(0.017)
3-Year Effect, λ_{1999}	0.022	-0.005	-0.002	-0.034
	(0.015)	(0.023)	(0.016)	(0.018)
5-Year Effect, λ_{2001}	0.024	0.004	-0.020	-0.060
	(0.015)	(0.022)	(0.016)	(0.019)
8-Year Effect, λ_{2004}	0.037	-0.011	-0.003	-0.102
	(0.015)	(0.024)	(0.022)	(0.025)
Implied Impact				
Using In-sample Variation[a]	0.002	-0.0004	-0.001	-0.005
Aggregate Impact, West Germany[b]	6,446	-1,014	-3,449	-13,301
Using Out-of-sample Variation[c]	0.018	-0.003	-0.009	-0.036
Aggregate Impact, West Germany[b]	48,720	-7,665	-26,069	-100,525
Level of Outcome in 1993				
Mean	0.026	0.092	0.049	0.057
S.D.	(0.012)	(0.041)	(0.018)	(0.021)
No. of Observations	8,050	8,050	8,050	8,050

[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 $\geq 1\%$ in 1993.

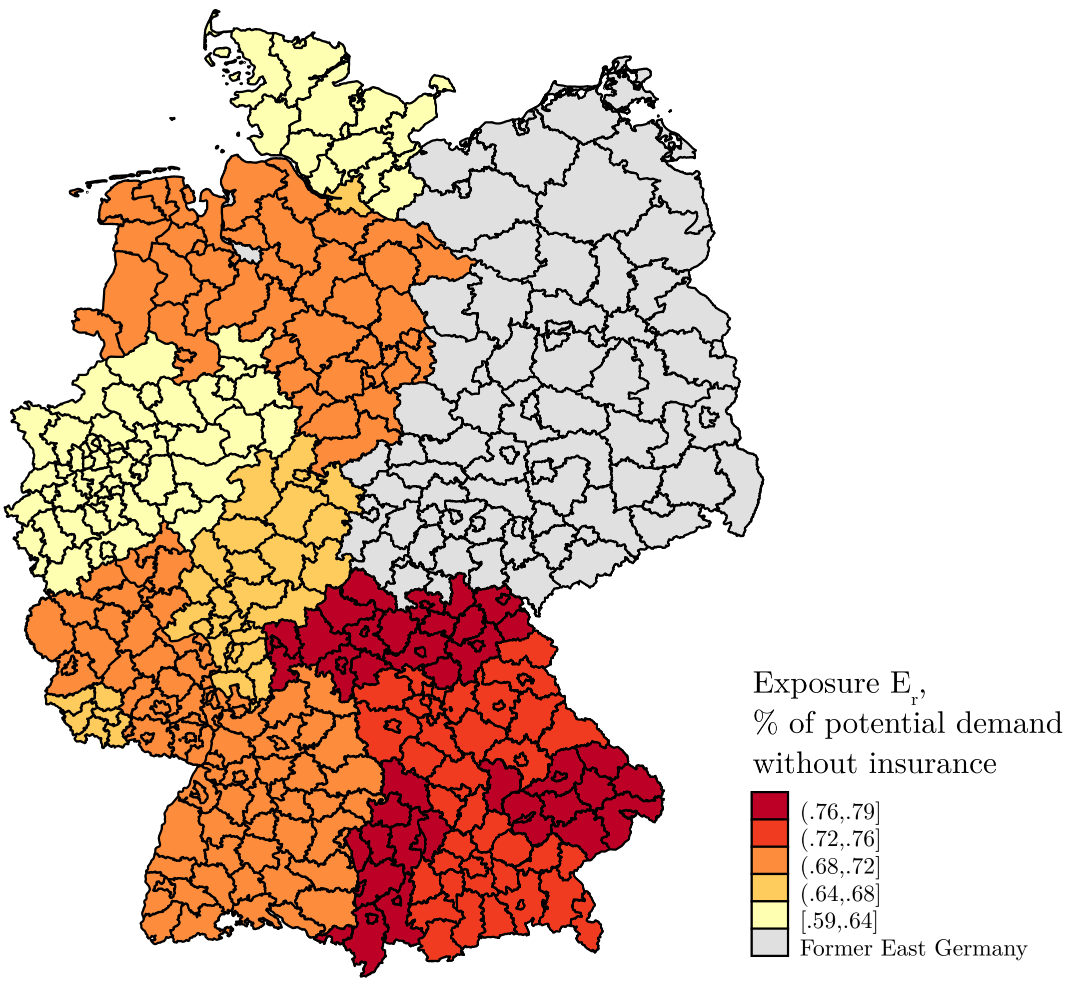
[c] Multiplies δ_{97-08} by the mean of the exposure variable across counties, $\mathrm{E}_r = 0.686$.

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 $\geq 1\%$. Hiring probabilities were estimated using the classification tree model outlined in Appendix Section C, with further details displayed in A.7.

ONLINE APPENDIX

A Figures and tables

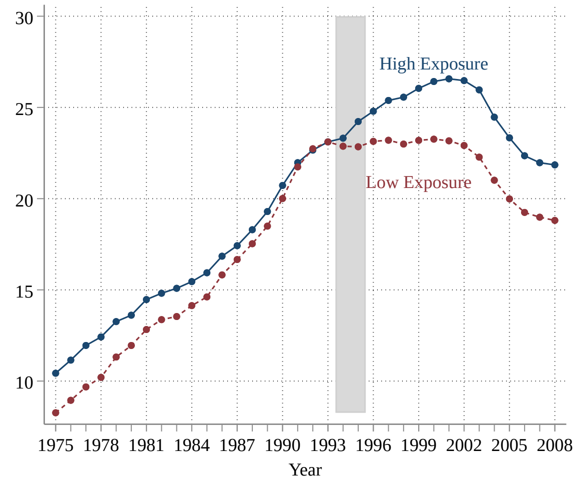
Figure A.1: Geographic Variation in Exposure



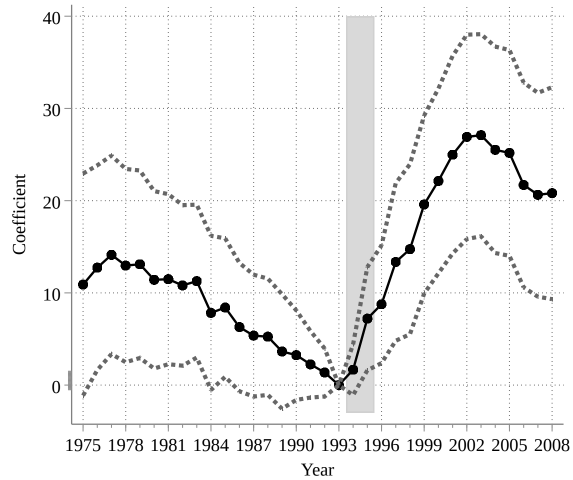
Notes: The share of individuals in need of long-term care, who did not have means-tested support for long-term care services in 1993, prior to 1995-1996 rollout of universal LTC insurance. The measure, denoted with E_r throughout the text is derived in Equation (1). We maps shows E_r for 322 West German counties in 15 exposure regions, excluding Berlin and Bremen.

Figure A.2: Universal LTC Insurance and Supply of SNF Care, by Type of Employment

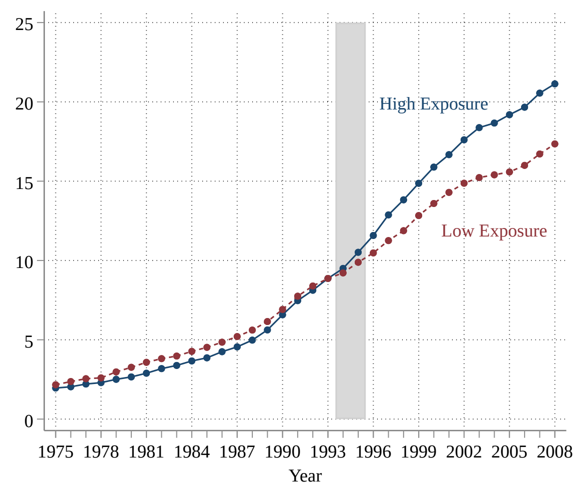
(A) Full-Time Workers per 1,000 65+ Population



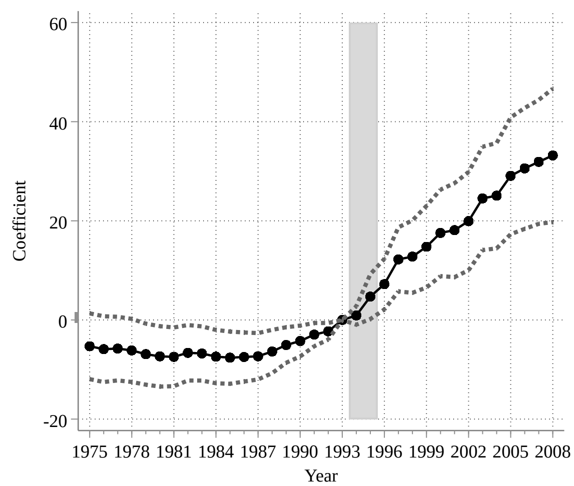
(B) Part-Time Workers per 1,000 65+ Population



(C) Full-Time Workers, Event Study



(D) Part-Time Workers, Eventy Study

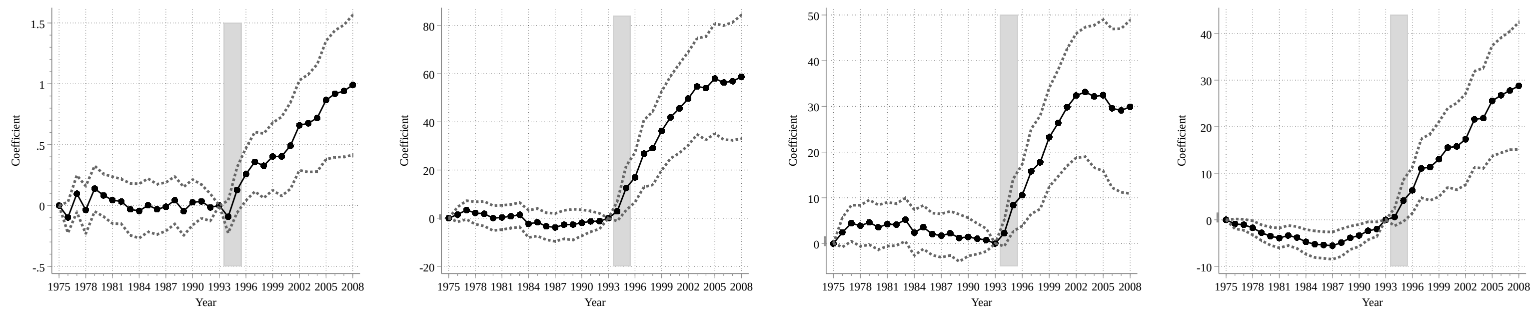


Notes: The top panels plot the average—across counties—number of SNF full-time (panel A) and part-time (panel B) workers per 1,000 individuals age 65+ and over, in 1975-2008. The county-level average is computed separately for the group of West German counties with (region-level) exposure variable E_r 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 λ_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 λ_t were normalized to zero in the pre-reform year t = 1993. λ_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.3: Introduction of Universal LTC Insurance and Supply of SNF Care: Alternative Specifications

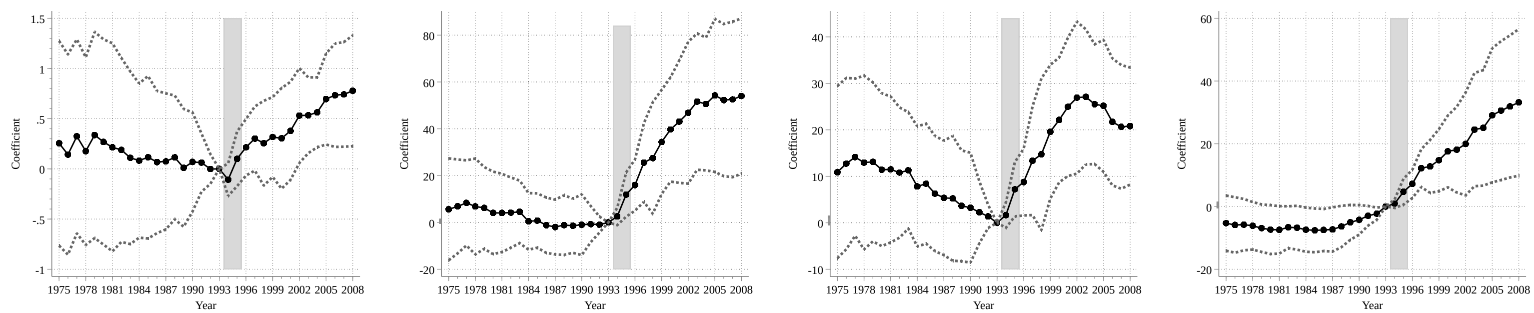
I. County-Specific Time Trend

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



II. S.E. Clustered at Region r Level, at which Exposure E_r varies

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

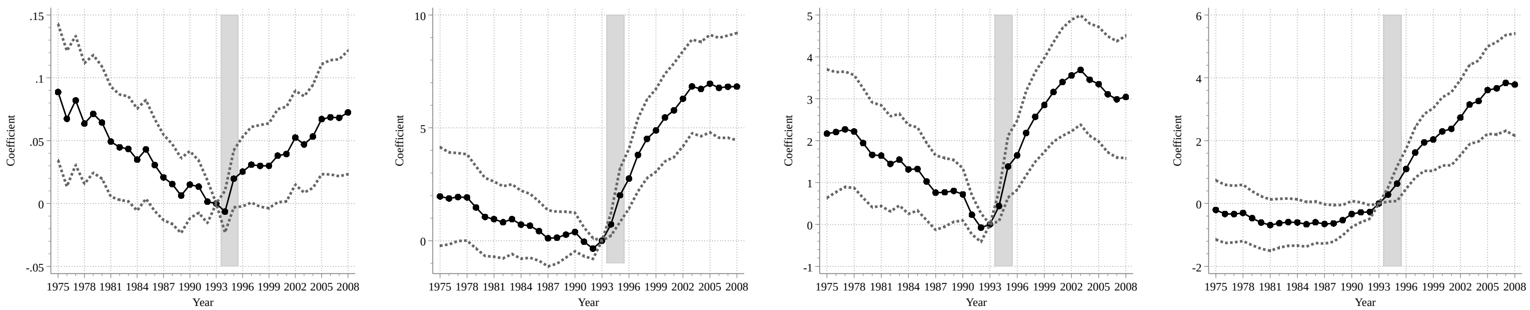


Notes: All panels display λ_t coefficients and 95% confidence intervals from estimating variations—as specified above the panels—of the specification in Equation 2 with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients λ_t were normalized to zero in the pre-reform year $t = 1993$. λ_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 **??**.

Figure A.4: Introduction of Universal LTC Insurance and Supply of SNF Care: Alternative Specifications

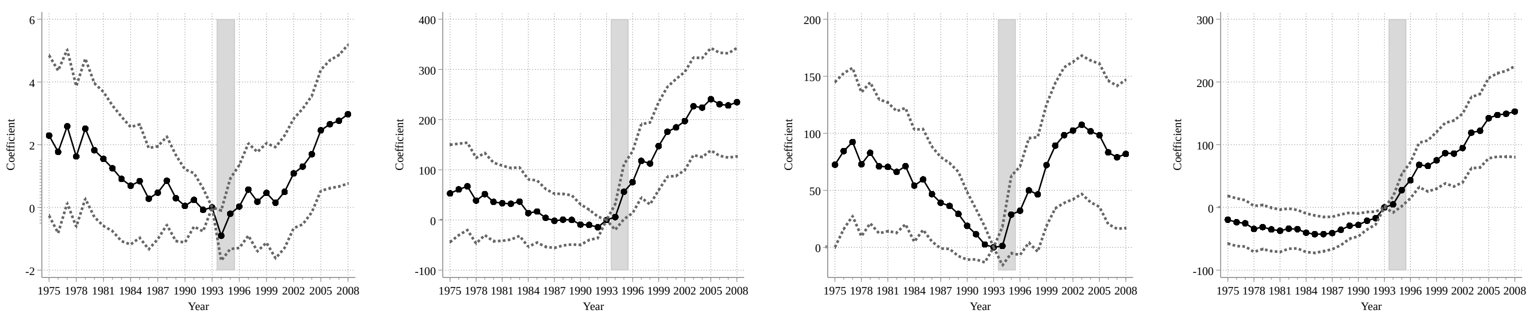
III. Binary Exposure Measure

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



IV. Alternative Exposure Measure (I): $E_r = 100\% - \frac{HzP_{r,1993}}{65andOlderPopulation_{r,1993}}$.

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

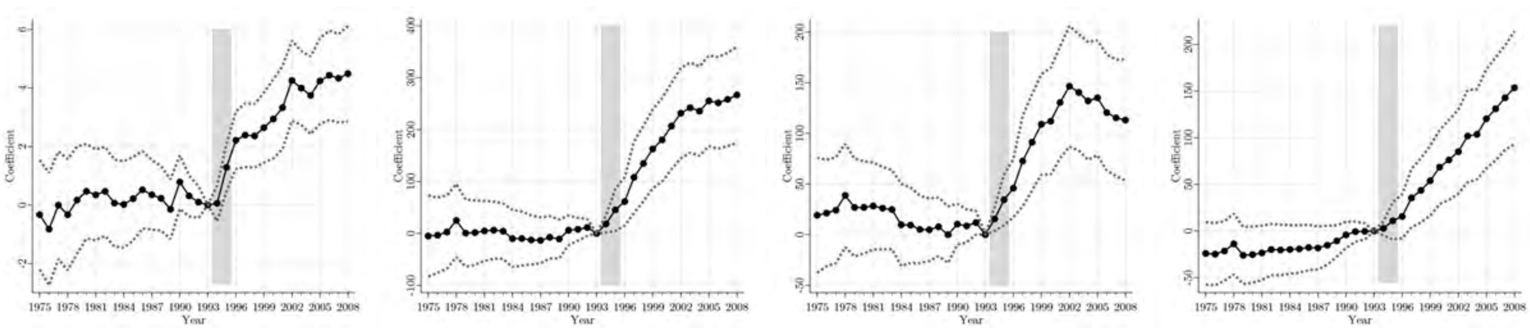


Notes: All panels display λ_t coefficients and 95% confidence intervals from estimating the specification in Equation 2 with an alternative measures of exposure to the reform, with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients λ_t were normalized to zero in the pre-reform year $t = 1993$. The binary exposure measure 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 alternative exposure measure (I) is defined as $E_r = 100\% - \frac{HzP_{r,1993}}{65andOlderPopulation_{r,1993}}$ (mean of $E_r = 0.953$). The mean of outcome variables in 1993 is reported in Table A2.

Figure A.5: Introduction of Universal LTC Insurance and Supply of SNF Care: Alternative Specifications

V. Alternative Exposure Measure (II): $E_r = \frac{g_{r,1993,1999} * LTCClaims_{r,1999} - HzP_{r,1993}}{65andOlderPopulation_{r,1993}}$

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

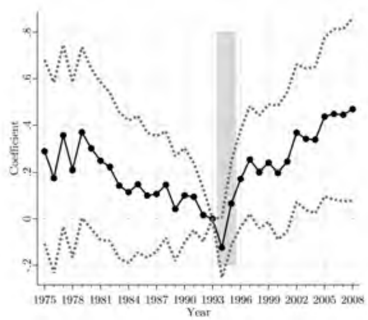


Notes: All panels display λ_t coefficients and 95% confidence intervals from estimating the specification in Equation 2 with an alternative measure of exposure to the reform, with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients λ_t were normalized to zero in the pre-reform year $t = 1993$. The alternative exposure measure (II) is defined as $E_r = \frac{g_{r,1993,1999} * LTCClaims_{r,1999} - HzP_{r,1993}}{65andOlderPopulation_{r,1993}}$ (mean of $E_r = 0.103$). The mean of outcome variables in 1993 is reported in Table A2.

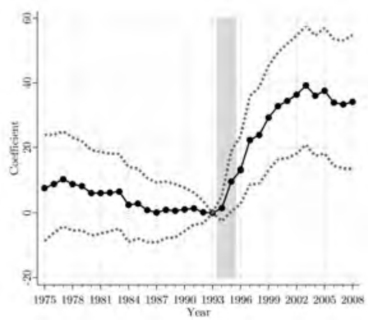
Figure A.6: Introduction of Universal LTC Insurance and Supply of SNF Care: Alternative Specifications

VI. Controlling for the County-Year-Level Count of Elderly

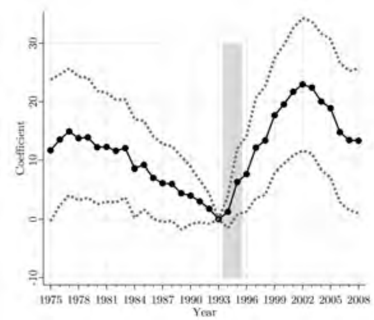
(A) SNF Firms



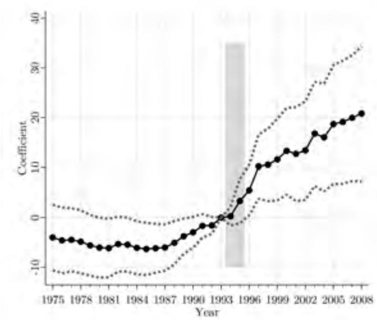
(B) SNF Workers



(C) SNF Full-Time Workers

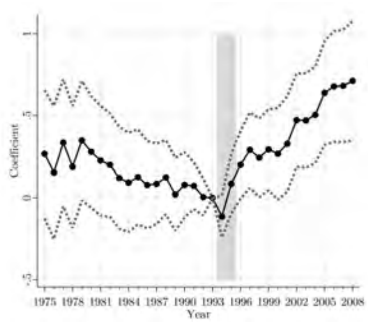


(D) SNF Part-Time Workers

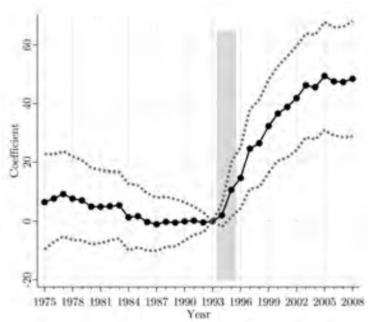


VII. Controlling for the County-Year-Level Share of Elderly

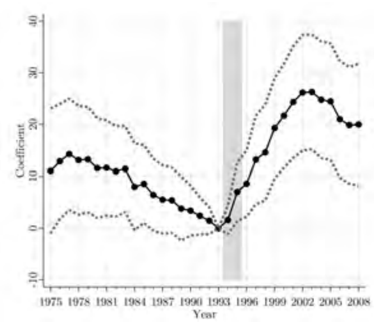
(E) SNF Firms



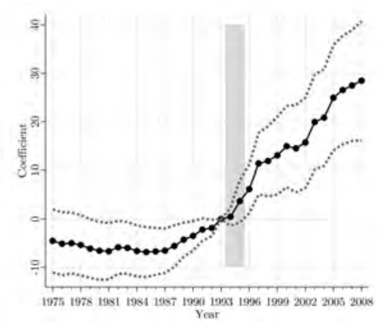
(F) SNF Workers



(G) SNF Full-Time Workers



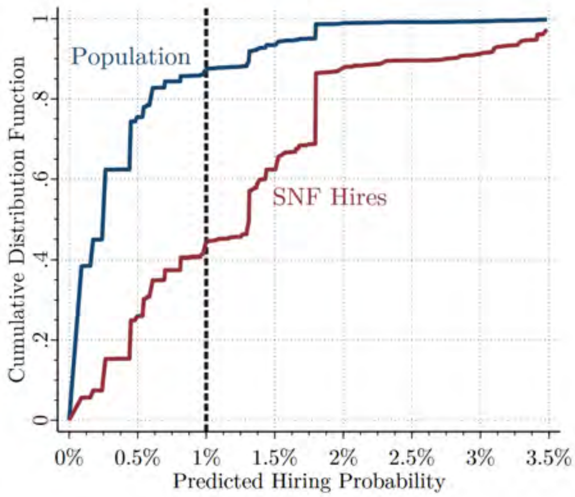
(H) SNF Part-Time Workers



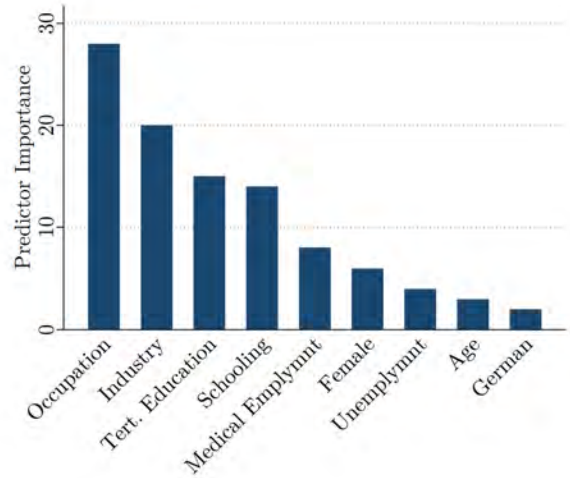
Notes: All panels display λ_t coefficients and 95% confidence intervals from estimating variations—as specified above the panels—of the specification in Equation 2 with the number of SNF firms, all workers, full-time workers, and part-time workers as outcomes, as specified in the panel title. Coefficients λ_t were normalized to zero in the pre-reform year $t = 1993$. λ_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.

Figure A.7: Characteristics of the CART Algorithm

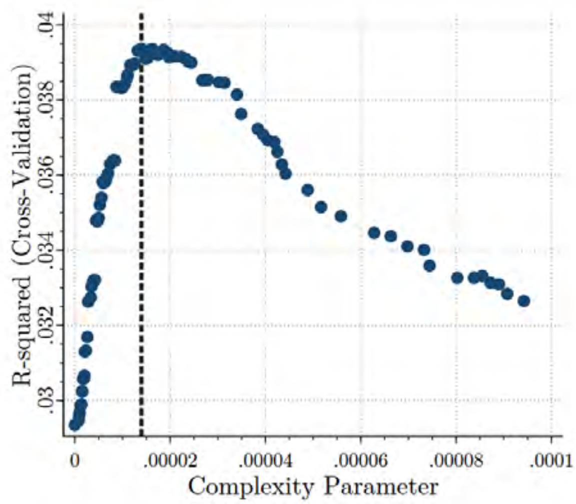
(A) CDF of Predicted SNF Hiring Risk



(B) Predictor Importance



(C) Complexity Parameter and Fit



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

	Outcome (per 1,000 Age 65+ Population)							
	County-Specific Time Trend				S.E. Clustered at Region r Level			
	Firms	Workers	Full-time	Part-time	Firms	Workers	Full-time	Part-time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled Coefficients								
δ_{97-08}	0.40	39.98	22.71	17.26	0.51	44.37	21.89	22.48
	(0.15)	(8.51)	(5.84)	(4.05)	(0.17)	(12.39)	(6.19)	(7.23)
Event Study Results								
1-Year Effect, λ_{1997}	0.36	26.83	15.78	11.05	0.30	25.58	13.36	12.23
	(0.12)	(7.05)	(4.73)	(3.21)	(0.15)	(7.82)	(5.46)	(2.80)
3-Year Effect, λ_{1999}	0.40	36.23	23.22	13.01	0.32	34.37	19.59	14.78
	(0.14)	(8.34)	(5.50)	(4.09)	(0.19)	(10.37)	(6.71)	(4.62)
5-Year Effect, λ_{2001}	0.49	45.59	29.82	15.76	0.38	43.10	24.98	18.12
	(0.18)	(9.42)	(6.51)	(4.73)	(0.23)	(12.22)	(6.95)	(6.36)
10-Year Effect, λ_{2006}	0.92	56.32	29.58	26.75	0.73	52.28	21.70	30.58
	(0.26)	(12.04)	(8.83)	(6.29)	(0.24)	(15.15)	(6.37)	(10.32)
Implied Impact								
Using In-sample Variation[a]	0.04	3.63	2.06	1.57	0.05	4.03	1.99	2.04
Aggregate Impact, West Germany[b]	352	35,193	19,995	15,198	450	39,058	19,268	19,789
Using Out-of-sample Variation[c]	0.27	27.44	15.59	11.85	0.35	30.45	15.02	15.43
Aggregate Impact, West Germany[b]	2,659	265,985	151,119	114,867	3,402	295,192	145,627	149,565
Level of Outcome in 1993								
Mean	0.77	31.98	23.11	8.87	0.77	31.98	23.11	8.87
S.D.	0.34	13.58	10.11	4.52	0.34	13.58	10.11	4.52
No. of Observations	10,948	10,948	10,948	10,948	10,948	10,948	10,948	10,948

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

	Outcome (per 1,000 Age 65+ Population)											
	Binary Exposure Measure[a]				Alternative Exposure Measure (I)[b]				Alternative Exposure Measure (II)[c]			
	Firms	Workers	Full-time	Part-time	Firms	Workers	Full-time	Part-time	Firms	Workers	Full-time	Part-time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pooled Coefficients												
δ_{97-08}	0.05	5.97	3.11	2.86	1.40	193.29	84.17	109.12	3.60	211.26	118.20	93.06
	(0.02)	(0.97)	(0.59)	(0.59)	(0.83)	(45.57)	(27.39)	(26.90)	(0.58)	(40.23)	(25.87)	(22.20)
Event Study Results												
1-Year Effect, λ_{1997}	0.03	3.80	2.18	1.62	0.57	117.72	49.93	67.79	2.39	108.15	72.69	35.46
	(0.02)	(0.82)	(0.51)	(0.41)	(0.75)	(37.19)	(23.26)	(17.98)	(0.56)	(35.02)	(22.75)	(15.95)
3-Year Effect, λ_{1999}	0.03	4.89	2.85	2.04	0.46	147.29	72.16	75.13	2.64	162.85	108.93	53.92
	(0.02)	(0.93)	(0.57)	(0.51)	(0.81)	(44.54)	(27.06)	(22.98)	(0.61)	(38.75)	(25.19)	(19.07)
5-Year Effect, λ_{2001}	0.04	5.78	3.40	2.38	0.50	184.39	98.43	85.97	3.33	206.84	130.57	76.27
	(0.02)	(1.06)	(0.65)	(0.59)	(0.91)	(49.05)	(30.21)	(26.68)	(0.72)	(42.31)	(28.06)	(21.80)
10-Year Effect, λ_{2006}	0.07	6.77	3.11	3.67	2.65	230.58	83.23	147.36	4.43	251.61	120.53	131.09
	(0.02)	(1.13)	(0.70)	(0.75)	(1.04)	(52.16)	(31.97)	(33.79)	(0.78)	(44.93)	(29.10)	(28.09)
Implied Impact												
Using In-sample Variation[d]	0.05	5.97	3.11	2.86	0.02	2.87	1.25	1.62	0.08	4.49	2.51	1.98
Aggregate Impact, West Germany[e]	483	57,896	30,173	27,723	202	27,846	12,126	15,720	742	43,568	24,377	19,191
Level of Outcome in 1993												
Mean	0.77	31.98	23.11	8.87	0.77	31.98	23.11	8.87	0.77	31.98	23.11	8.87
S.D.	0.34	13.58	10.11	4.52	0.34	13.58	10.11	4.52	0.34	13.58	10.11	4.52
No. of Observations	10,948	10,948	10,948	10,948	10,948	10,948	10,948	10,948	10,948	10,948	10,948	10,948

[a] 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.
[b] The alternative exposure measure (I) is defined as $E_r = 100\% - \frac{HzP_{r,1993}}{65andOlderPopulation_{r,1993}}$.
[c] The alternative exposure measure (II) is defined as $E_r = \frac{g_{r,1993,1999} * LTCClaims_{r,1999} - HzP_{r,1993}}{65andOlderPopulation_{r,1993}}$.
[d] The "In-sample impact" of the reform on the per capita outcome of interest uses variation in exposure across regions. We multiply δ_{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.
[e] 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 δ_{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 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.

Table A3: Event Study Results: Aggregate Response, Alternative Specifications

	Outcome (per 1,000 Age 65+ Population)							
	Controlling for Count of Elderly				Controlling for Share of Elderly			
	Firms	Workers	Full-time	Part-time	Firms	Workers	Full-time	Part-time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled Coefficients								
δ_{97-08}	0.32	32.43	17.53	14.90	0.46	40.37	21.27	19.10
	(0.14)	(8.43)	(5.06)	(4.78)	(0.13)	(8.28)	(5.00)	(4.57)
Event Study Results								
1-Year Effect, λ_{1997}	0.25	22.34	12.13	10.21	0.29	24.57	13.20	11.36
	(0.12)	(6.89)	(4.34)	(3.25)	(0.12)	(6.87)	(4.34)	(3.22)
3-Year Effect, λ_{1999}	0.24	29.26	17.66	11.59	0.29	32.31	19.28	13.03
	(0.13)	(8.16)	(4.96)	(4.16)	(0.12)	(8.05)	(4.93)	(4.05)
5-Year Effect, λ_{2001}	0.24	34.41	21.70	12.71	0.33	38.83	24.33	14.50
	(0.15)	(8.97)	(5.54)	(4.78)	(0.15)	(8.77)	(5.49)	(4.56)
10-Year Effect, λ_{2006}	0.45	33.90	14.78	19.13	0.68	47.56	20.99	26.57
	(0.19)	(9.94)	(6.02)	(6.27)	(0.17)	(9.41)	(5.73)	(5.70)
Implied Impact								
Using In-sample Variation [a]	0.03	2.95	1.59	1.35	0.04	3.67	1.93	1.73
Aggregate Impact, West Germany[b]	283	28,551	15,436	13,115	408	35,540	18,723	16,817
Using Out-of-sample Variation[c]	0.22	22.26	12.03	10.23	0.32	27.71	14.60	13.11
Aggregate Impact, West Germany[b]	2,141	215,784	116,661	99,123	3,085	268,605	141,508	127,097
Level of Outcome in 1993								
Mean	0.77	31.98	23.11	8.87	0.77	31.98	23.11	8.87
S.D.	0.34	13.58	10.11	4.52	0.34	13.58	10.11	4.52
No. of Observations	10,948	10,948	10,948	10,948	10,948	10,948	10,948	10,948

[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] Scales estimates by 9,693 thousand people age 65+ in West Germany (excluding Berlin and Bremen) in 1993.
[c] Multiplies δ_{97-08} by the mean of the exposure variable across counties, $\mathrm{E}_r = 0.686$.

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 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 $t = 1993$. 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

	Outcome (per 1,000 Age 65+ Population)					
	Count New SNF Hires[a]	Among New SNF Hires[a], Count of				
		Employed & in HC in t-1	Employed & not in HC in t-1	Unemployed in t-1	Temproarily Not in Labor Force in t-1	Not Yet in Data in t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Coefficients						
δ_{97-08}	8.69	0.67	1.16	2.04	3.83	1.00
	(1.92)	(0.75)	(0.58)	(0.43)	(0.53)	(0.42)
Event Study Results						
1-Year Effect, λ_{1997}	8.74	3.19	0.23	2.48	2.43	0.40
	(4.28)	(3.23)	(0.89)	(0.60)	(0.54)	(0.49)
3-Year Effect, λ_{1999}	6.75	0.01	1.35	1.76	2.95	0.68
	(2.16)	(0.80)	(0.65)	(0.58)	(0.67)	(0.49)
5-Year Effect, λ_{2001}	9.11	-0.27	2.32	2.06	3.45	1.55
	(2.33)	(1.03)	(0.72)	(0.53)	(0.71)	(0.47)
10-Year Effect, λ_{2006}	8.98	1.31	0.69	2.30	3.49	1.20
	(2.25)	(1.03)	(0.71)	(0.51)	(0.62)	(0.54)
Implied Impact						
Using In-sample Variation[a]	0.79	0.06	0.11	0.19	0.35	0.09
Aggregate Impact, West Germany[b]	7,651	586	1,020	1,798	3,370	877
Using Out-of-sample Variation[c]	5.97	0.46	0.80	1.40	2.63	0.68
Aggregate Impact, West Germany[b]	57,826	4,430	7,707	13,590	25,474	6,625
Level of Outcome in 1993						
Mean	6.44	1.00	1.33	1.10	1.98	1.03
S.D.	2.80	0.72	0.81	0.62	0.90	0.61
No. of 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] Multiplies 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] Multiplies δ_{97-08} by the mean of the exposure variable across counties, $\mathrm{E}_r = 0.686$.

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. 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.

Table A5: Event Study Results: Count of New SNF Hires By Characteristics

	Outcome (per 1,000 Age 65+ Population)					
	Count of New SNF Hires[a]	Among New SNF Hires[a], Count of				
		Abitur Holders	Germans	Females	Part-time Employees	Apprentices in t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Coefficients						
δ_{97-08}	8.69	0.28	8.33	7.54	2.72	-0.24
	(1.92)	(0.28)	(1.74)	(1.56)	(0.84)	(0.17)
Event Study Results						
1-Year Effect, λ_{1997}	8.74	0.48	8.36	8.22	3.44	0.32
	(4.28)	(0.42)	(4.11)	(3.51)	(1.63)	(0.19)
3-Year Effect, λ_{1999}	6.75	0.28	6.60	6.11	1.21	-0.77
	(2.16)	(0.39)	(2.00)	(1.78)	(0.96)	(0.24)
5-Year Effect, λ_{2001}	9.11	0.28	8.67	8.15	1.29	-0.09
	(2.33)	(0.41)	(2.17)	(1.81)	(1.08)	(0.21)
10-Year Effect, λ_{2006}	7.89	0.22	7.43	6.79	3.40	-0.38
	(2.31)	(0.34)	(2.11)	(1.92)	1.16	(0.21)
Implied Impact						
Using In-sample Variation[a]	0.79	0.03	0.76	0.69	0.25	-0.02
Aggregate Impact, West Germany[b]	7,651	243	7,330	6,642	2,393	-209
Using Out-of-sample Variation[c]	5.97	0.19	5.71	5.18	1.87	-0.16
Aggregate Impact, West Germany[b]	57,826	1,838	55,395	50,198	18,090	-1,581
Level of Outcome in 1993						
Mean	6.44	0.57	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] Multiplies 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] 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. 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.[31]

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.

[31] 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 a 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 one 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 eight (Upper secondary school leaving certificate from a specialised 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 "one" 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 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; and 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.

6. Schooling.

   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 voc. 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.

9. Two-digit occupation code according to KldB1988.

   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.