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Article (Accepted version) (Refereed)

Original citation:
Hu, Yaoyue and Leinonen, Taina and Myrskylä, Mikko and Martikainen, Pekka (2018) *Changes in socioeconomic differences in hospital days with age: cumulative disadvantage, age-as-leveler, or both?* Journals of Gerontology - Series B Psychological Sciences and Social Sciences. ISSN 1079-5014

DOI: 10.1093/geronb/gbx161

Changes in socioeconomic differences in hospital days with increasing age: Cumulative disadvantage, age-as-leveler, or both?

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Funding

This work is supported by European Research Council Starting Grant to Mikko Myrskylä (COSTPOST) [#336475]. The research leading to this publication has been supported by the Max Planck Society within the framework of the project "On the edge of societies: New vulnerable populations, emerging challenges for social policies and future demands for social innovation. The experience of the Baltic Sea States" (2016-2021). PM is funded by the

Academy of Finland, Strategic Research Council PROMEQ project (#303615) and the Signe and Ane Gyllenberg Foundation.

Acknowledgment

The authors would like to thank Statistics Finland and the National Institute for Health and Welfare for providing the data.

Author Contributions

YH and PM conceptualized the research project. YH performed the data analysis and drafted the manuscript. YH , TL, MM, and PM interpreted the results. TL, MM, and PM critically revised and commented on all versions of the manuscript. All authors approved the final version of the manuscript.

Conflict of interest

None.

Abstract

Objectives: Length of hospital stay is inversely associated with socioeconomic status (SES). It is less clear whether socioeconomic disparities in numbers of hospital days diverge or converge with age.

Method: Longitudinal linked Finnish registry data (1988-2007) from 137,653 men and women aged 50-79 at the end of 1987 were used. Trajectories of annual total hospital days by education, household income, and occupational class were estimated using negative binomial models.

Results: Men and women with higher education, household income, and occupational class had fewer hospital days in 1988 than those with lower SES. Hospital days increased in 1988-2007. For some age groups, higher SES was associated with a faster annual rate of increase, resulting in narrowing rate ratios of hospital days between SES groups (relative differences); the rate ratios remained stable for other groups. Absolute SES differences in numbers of hospital days appeared to diverge with age among those aged 50-69 years at baseline, but converge among those aged 70-79 years at baseline.

Discussion: The hypotheses that socioeconomic disparities in health diverge or converge with age may not be mutually exclusive; we demonstrated convergence/maintenance in relative differences for all age groups, but divergence or convergence in absolute differences depending on age.

Key words: socioeconomic disparities, hospital days, longitudinal registry-based data

Introduction

Population aging is a global phenomenon, and a major challenge for the sustainability of healthcare and social security systems (Rechel et al., 2013; World Health Organization, 2015). Ensuing that older adults remain in good health as long as possible not only improves the quality of life for the aging population; but also buffer against the expected cost pressures on the care system (Rechel et al., 2013; World Health Organization, 2015). Research on the determinants of healthy aging can greatly contribute to this goal.

Socioeconomic status (SES) is one of the most established and persistent determinants of health for older adults. SES is multi-dimensional and can be reflected by education, occupation, and income. These SES indicators are correlated but they represent different types of resources and are associated with health through both shared and independent pathways (Braveman, Egerter, & Williams, 2011). Education is clearly associated with employment opportunities, access to information and ability to process information, ability to develop and change behaviors, and control of life. Occupation is linked with physical working environment, employment-related earnings and benefits, and work-related stress and social support. Whereas income is related to direct access to health care, nutrition, housing, transport and other resources. As a result, to better understand how SES is linked to health, it is beneficial to investigate various SES indicators.

For high income countries, 55% of the total loss of disability-adjusted life years in 2015 was attributable to health conditions among older population aged 60+ (World Health Organization, 2016). Reducing health differentials at older ages and improving health of the more disadvantaged older adults in particular could reduce the total disease burden and ameliorate health of the whole population (Feinstein, 1993; Grundy & Sloggett, 2003; Huisman, Kunst, & Mackenbach, 2003; Marmot, 2005; World Health Organization, 2015).

A number of studies have examined how socioeconomic disparities in health change with increasing age among older adults, but the evidence remains mixed (Corna, 2013; Pavalko & Wilson, 2011). Some studies have found that socioeconomic disparities in health increase with age, i.e., a further divergence of health differentials between SES groups or the effect of SES on health increases with age (Dupre, 2007; Lynch, 2003; Mirowsky & Ross, 2008; Willson, Shuey, & Elder, 2007). The finding of a further divergence of health supports the cumulative advantages/disadvantages (CAD) hypothesis: the advantages/disadvantages in social, economic, behavioral, and psychosocial resources gradually accumulate over the life course and thus produce the enlarging differences in health with increasing age.

However, a narrowing gap of health between SES groups with increasing age also have been reported in previous studies, i.e., a convergence of the health differentials between SES groups or the effect of SES on health diminishes with age (Herd, 2006; House et al., 1994; Ross & Wu, 1996). The observation of a convergence of health provides evidence for the age-as-leveler (AAL) hypothesis: there is a biological ceiling in late life that older adults from different SES groups become universally fragile with increasing age, placing less importance of social determinants to aging. The convergence, however, can also be related to mortality selection that less healthy people from lower SES groups to die prematurely than their counterparts from higher SES groups (Beckett, 2000; Lauderdale, 2001). Still other studies have shown that there are constant socioeconomic gaps in health at older ages (status maintenance) (Leopold & Engelhartdt, 2013; Pavalko & Wilson, 2011; Stolz, Mayerl, Waxenegger, Rasky, & Freidl, 2017).

The inconsistency of these findings is largely attributable to differences in study design; i.e., to differences in the health outcomes studied and in whether the data used were cross-sectional or longitudinal (Leopold & Engelhartdt, 2013; Pavalko & Wilson, 2011). Cross-sectional data provide only a snapshot of age-specific health patterns; whereas the comparability of longitudinal studies is hampered by the varying characteristics of the study samples (e.g., countries and age groups) and the statistical methods used to analyze the data. Long-term panel data are preferable when investigating changes in socioeconomic differences in health at older ages, as they allow for the separation of age and birth cohort effects (Dupre, 2007; House, Lantz, & Herd, 2005; Leopold & Engelhartdt, 2013; Pavalko & Wilson, 2011). However, problems related to non-response and attrition can threaten the validity of findings from panel studies; an issue that only a few studies have addressed explicitly (Howe, Tilling, Galobardes, & Lawlor, 2013; Lynch & Brown, 2011; Pavalko & Wilson, 2011; Willson et al., 2007).

The association between SES and health are often measured by relative difference and absolute difference. Relative difference focuses on the equality, independent of the actual level of health in each SES group; whereas absolute difference emphasizes the difference in the actual level of health between lower and higher SES groups (Mackenbach, 2015). It is important, if possible, to estimate both absolute and relative SES differences in health for better monitoring of health inequalities, evaluating policy interventions, and improving our understanding of the causes of health differentials (Regidor, 2004). However, we are not aware of research on changes in relative differences in health with increasing age using long-term longitudinal data with repeated measures of health. It remains unclear whether the changes of absolute and relative SES differences in health with increasing age are similar to those observed for mortality; i.e. exhibiting opposing trends for the relative and the absolute difference with age (Bor, Cohen, & Galea, 2017; Mackenbach, Kulhanova, et al., 2016).

Older adults are disproportionately heavy users of health care and long-term care services (Wolinsky, Culler, Callahan, & Johnson, 1994; World Health Organization, 2015). Length of hospital stay, an important index of morbidity and resource consumption, has been found to be inversely associated with education, income, and occupational class (Epstein, Stern, &

Weissman, 1990; Liao, McGee, Kaufman, Cao, & Cooper, 1999; Roos & Mustard, 1997). The recent World Report on Ageing and Health (World Health Organization, 2015) revealed pronounced inequalities that, compared to more advantaged older adults, disadvantaged older adults have more difficulties accessing health services, over and above their higher health risks and more severe health problems. To our knowledge, no previous study has investigated either absolute or relative differences in changes in socioeconomic disparities in hospital use as individuals grow older. In this study, we examined these issues using 20 years of Finnish registry data.

Methods

Study population

We used data from a linked register-based 11% random sample of the population residing in Finland at the end of each year between 1987 and 2007. We restricted our study population to individuals aged 50-79 at the end of 1987 (i.e., born between January 1908 and December 1937). We also excluded individuals who 1) were not part of the dwelling population of Finland (e.g., being institutionalized or imprisoned) at the end of 1985 or 1987; 2) were not residing in Finland at the end of each year in the 1987-2007 period; or 3) had died in 1988 with no hospitalizations as they contributed no information towards hospital use in the 1988-2007 period. The final size of the study population was 137,653 (59,586 men and 78,067 women). The cohort was followed up annually in 1988-2007.

Hospital days

Hospitalization episodes between January 1, 1988, and December 31, 2007, were extracted from hospital discharge records. We calculated total number of hospital days for each year of 1988-2007. The annual hospital days could include multiple hospitalization episodes in a given year, and the days from all episodes were added up. If no hospitalization occurred in a given year, the number of hospital days was coded as zero.

Socioeconomic status

To reflect the multi-dimensional nature of SES, we selected three indicators from the labor market file: highest educational attainment, household income, and occupational class.

Information on highest educational attainment and household income were measured at the end of 1987. Individuals with basic education (i.e., less than upper secondary school) were the dominant group. We thus dichotomized educational attainment into basic education and beyond basic education (i.e., upper secondary school or higher). Household income was derived by dividing the taxable household income by the number of consumption units in the household using the Organisation for Economic Co-operation and Development (OECD)-modified scale (Hagenaars, de Vos, & Zaidi, 1994). Household income was further categorized into tertiles by sex and five-year age groups.

Information on occupational class was available every five years, and we used the most recent information measured at the end of 1985 to our baseline (i.e., between the end of 1987 and the end of 1988). The occupational classes were as follows: non-specialized manual class or specialization unknown, specialized manual class, white-collar class, and other (including farmers, self-employed, students, other occupational classes, or occupational class unknown). For individuals who were retired or unemployed in 1985, the most recent information available on their previous occupational class was used.

Covariates

Native language and region of residence were controlled as covariates. Native language was time-invariant, and was dichotomized into Finnish and Swedish or other languages. Region of residence was time-varying, and was updated annually at the end of each year in the 1987-2007 period. In line with Statistics Finland, we used the following region of residence categories: eastern, western, southern, and northern Finland.

Statistical analysis

In each year of the 1988-2007 period, the distribution of hospital days was highly skewed, as 66%-80% of our study population was not hospitalized (i.e., had zero hospital days). We modeled the hospital days as a count response. The over-dispersion and the excess of zeroes of hospital days can be handled by using the negative binomial (NB) model and two zero-altered models: the zero-inflated Poisson (ZIP) model and the zero-inflated negative binomial (ZINB) model (Hilbe, 2007). We compared the model fit of the three models using information criteria, and found that the ZIP and ZINB models did not outperform the NB model. We therefore used the most parsimonious NB model throughout this study. The key variables in the NB model are 1) the intercept, which captures the hospital days at baseline (i.e., the year 1988 coded as time zero); and 2) the slope, which represents the annual rate of change in hospital days over the follow-up years (i.e., the years 1989-2007 coded as time 1-19, respectively). All models were fitted using Mplus 7 (Muthén & Muthén, 1998-2015). For more details on the model comparison, see section 1.1 of the supplementary materials.

The “empty” model containing only the intercept and the slope was fitted first with no SES indicators or covariates (unconditional models). Because of the log link function used in the NB models, the exponentiated estimates of the intercept and the slope respectively represent the expected hospital days at baseline and the expected annual rate of increase in hospital days over the follow-up period. The hospital day trajectories over the years 1988-2007 were thus exponential on the scale of actual days (Liu & Powers, 2007). Both the intercept and the slope were then regressed on education, household income, and occupational class; adjusting for native language and region of residence (conditional models). The models were fitted separately for each SES indicator, for men and women, and for three age groups at baseline (50-59, 60-69, and 70-79).

As a measure of relative difference, the exponentiated coefficients of the intercept and the slope for the SES indicators (conditional models) respectively represent the ratio of expected hospital days at baseline and the ratio of the expected annual rate of increase in hospital days between the SES groups. The absolute SES differences in hospital days at baseline and changes in these differences over the follow-up period were plotted in figures.

Results

Table 1 summarizes the socio-demographic characteristics of our study population at baseline, as well as the mean hospital days in each year of the 1988-2007 period. The men in our study population were younger than the women. The mean hospital days at baseline were higher in older than in younger age groups. More than 70% of the study population had basic education. More women than men were in the white-collar class, and more men than women were in the specialized manual class. For both sexes, the mean hospital days at baseline were smaller in higher than in lower socioeconomic groups. The mean hospital days increased gradually with age. The mean hospital days was 5.06 days higher for men and 6.62 days higher for women in 2007 than in 1988.

[Table 1 here]

Tables 2 gives the results for the relationship between SES and trajectories of hospital days (relative difference) for men and for women. The unconditional estimates of both hospital days at baseline (i.e., intercept) and the annual rate of increase in hospital days (i.e., slope) from the “empty” models were similar for men and women aged 50-59 at baseline. On average, women aged 60-69 at baseline had fewer hospital days at baseline, but a faster rate of increase than their male counterparts (difference in the slope p <0.001). Women aged 70-79 at baseline had both more hospital days at baseline and a faster rate of increase (difference in the slope p =0.01) than men in the same age band.

As we can see from the conditional estimates, there was a clear gradient in the intercept indicating that among both sexes, individuals with higher education, household income, and occupational class had around 10%-60% fewer hospital days at baseline than their lower SES counterparts. However, among men, most of the differences in the intercept between occupational classes were not statistically significant.

For the slope, among some subgroups, higher SES was associated with a faster annual rate of increase in hospital days than lower SES. For example, the rate of increase was 2% faster for men aged 50-59 at baseline in the high household income tertile than for those in the low household income tertile (ratio of annual rate of increase: 1.02, 95% confidence interval [CI]: 1.01,1.03). For men aged 60-69 at baseline, being in the middle or high household income tertiles was associated with a 1% faster rate of increase than being in the low household income tertile (middle household income: 1.01, 95% CI: 1.00, 1.02; high household income: 1.01, 95% CI: 1.00, 1.03). For women aged 50-59 at baseline, being in the middle household income tertile was associated with a 1% faster rate of increase than being in the low household income tertile (1.01; 95% CI: 1.00, 1.02). For women aged 70-79 at baseline, compared to being in the non-specialized manual class/specialization unknown category, the rate of increase was 1% faster for being in the specialized manual class (1.01, 95% CI: 1.00, 1.03), and was 2% faster for being in the white-collar class (1.02, 95% CI: 1.00, 1.03). Accordingly, relative SES differences in hospital days diminished over the follow-up period for these subgroups. For other subgroups, relative SES differences appeared to be unchanged, given the statistically non-significant ratio of the rate of increase. The interactions of each

SES indicator with gender and with age were tested on both intercept and slope. The effect of SES on the trajectories of hospital days did not differ by age groups among either men or women, except for household income on the intercept (both gender p<0.001), for occupational class on the intercept (men p=0.04; women p<0.001), and for occupational class on the slope among women (p=0.02). Similarly, we did not find gender difference in the effect of SES for any age group, except for the intercept with occupational class for ages 50-59 (p=0.01) and 60-69 (p=0.03) and with education for ages 60-69 (p=0.04). The results from the pooled study population of men and women are shown in Supplementary Table 2.

[Table 2 here]

Figures 1-2 show absolute differences in hospital days by education and household income in 1988-2007 (see Supplementary Figure 2 for occupational class). While relative SES differences in hospital days largely maintained and only decreased in some subgroups, absolute differences appeared to enlarge over the 1988-2007 period among men and women aged 50-69 at baseline, but narrow among those aged 70-79 baseline.

[Figures 1-2 here]

Number of hospitalization episodes is another important aspect of hospital care. We repeated our analysis using the annual total number of hospitalization as outcome, and the findings were similar to those for hospital days (Supplementary Table 3). However, for both genders, the faster increase in the number of hospitalizations associated with higher education was found at ages 70-79 instead of 50-59. For women aged 70-79 faster increase in the number of hospitalization was associated with higher household income but not with occupational class. For the change of the absolute difference in the number of hospitalization between education groups, the tendency of a convergence at ages 70-79 became more evident (Supplementary Figure 3).

Over the follow-up period, 34,103 men and 36,631 women died. Hospital days were missing for these individuals after their deaths. Mplus handles missing data using full information maximum likelihood; a statistical estimation technique that is valid under the assumption of missing at random (MAR, i.e., missingness depends on covariates and the outcome variable observed at previous time points) (Muthén & Muthén, 1998-2015). If MAR does not hold, missing not at random (MNAR) models should be used to perform sensitivity analysis (for more details, see section 1.2 of the supplementary materials) (Muthén, Asparouhov, Hunter, & Leuchter, 2011). We therefore fitted pattern-mixture models within the framework of latent growth curve modeling (MNAR models), in which both the intercept and the slope were modeled as a function of indicators of the year of death (Little, 2009; Muthén et al., 2011). More details are provided in section 1.2 of the supplementary materials. The results of the pattern-mixture models deviated little from those of the MAR models (see results in Supplementary Tables 4). For both sexes and all age groups at baseline, relative SES differences for both the intercept and the slope were smaller in the pattern-mixture models than in the MAR models. The age-specific patterns of changes in absolute differences in the pattern-mixture models were generally consistent with those in the MAR models (Supplementary Figures 4-6). However, a continuous divergence was seen between household income tertiles and occupational classes for men aged 70-79 at baseline.

Discussion

In this study using large-scale longitudinal registry data, we found that older adults with higher education, household income, and occupational class had fewer hospital days at baseline than their counterparts with lower SES. Over 1989-2007, relative differences in hospital days declined between the lowest and higher household income tertiles for men aged 50-69 at baseline; between the lowest and the middle household income tertiles for women aged 50-59 at baseline; and between the non-specialized manual class and the specialized manual/white-collar class for women aged 70-79 at baseline. For the other subgroups, relative SES differences in hospital days were unchanged. There was, however, a further divergence in absolute differences in hospital days by education, household income, and occupational class groups for men and women aged 50-69 at baseline, but a convergence for those aged 70-79 at baseline.

Our findings suggest that the divergence and the convergence of socioeconomic disparities in health at older ages may not be mutually exclusive; rather, which trend is found may depend on the measurement scale of socioeconomic disparities in health (relative or absolute differences) and the ages used. Similar to previous observations on mortality (Bor et al., 2017; Mackenbach, Kulhanova, et al., 2016), for some SES subgroups at ages 50-69, we found that the relative difference narrowed while the absolute difference increased. For other subgroups, the relative difference remained stable at all ages, whereas the absolute difference increased at ages 50-69 but diminished at ages 70+. It is not straightforward to link these opposing trends to AAL, CAD, or status maintenance hypotheses because inference based on relative and absolute difference may lead to different conclusions. Mackenbach, Martikainen, Menvielle, & de Gelder (2016) showed that different combinations of starting levels and changes of mortality by SES groups over time lead to different patterns of changes in relative and in absolute differences in mortality. Our findings fall into one of these patterns. Whereas relative SES differences in hospital days maintained/diminished in 1988-2007, changes in absolute differences were less monotonic: absolute differences started to decline only after the ratio of hospital days in the higher vs. the lower SES group became larger than the ratio of the increase in hospital days in a year in the lower vs. the higher SES group. Since the opposing trends of change in relative and absolute difference are still not fully understood (Mackenbach, Martikainen, et al., 2016), it remains for further research to answer the question of which measurement scale, relative or absolute, is more appropriate to use for testing the AAL and CAD hypotheses. From the perspective of policy makers, actual absolute hospital days are a more relevant metric for policies aiming to reduce the SES differentials in hospital care and are more meaningful and easy to implement in monitoring success in policy interventions.

We compared our findings on changes in absolute differences with the results of selected previous studies that used longitudinal data with repeated measures and similar statistical analytic approaches (Benzeval, Green, & Leyland, 2011; Chandola, Ferrie, Sacker, & Marmot, 2007; Herd, 2006; Kim & Durden, 2007; Stolz et al., 2017; Willson et al., 2007). One study reported a continuous divergence in the relationship between employment grades and self-rated health trajectories in British civil servants aged 39-74 (Chandola et al., 2007), while another reported a continuous divergence in the relationship between education and income with physical impairment trajectories across ages 25-89 (Kim & Durden, 2007). But Stolz et al. (2017) found for Europeans aged 50+ stable differences in frailty with increasing age across educational, wealth, and occupational class groups, and decreasing differences across income groups. In line with our findings, other studies have shown that after diverging at earlier ages, gaps in physical functioning and self-rated health converge across educational groups and manual and non-manual classes when people reach their sixties or seventies (Benzeval et al., 2011; Herd, 2006; Willson et al., 2007).

Kim & Durden (2007) and Willson et al. (2007) are the only studies that covered most of the adult ages (ages 25-89 and 26-92, respectively); whereas the other studies tracked changes in socioeconomic disparities in health only until people reached their sixties or early seventies. Our data enabled us to follow men and women aged 50-59, 60-69, and 70-79 years over a 20-year period starting at the end of 1987; and thus until ages 70-79, 80-89, and 90-99, respectively. Moreover, we found important differences between the three 10-year age groups.

Kim & Durden (2007) assumed common physical impairment trajectories for all ages, even though 43% of their sample were aged 25-49 at baseline. Our results suggest that the divergence Kim & Durden (2007) found may be driven by these relatively healthy young adults, and that the convergence at older ages is hidden. Although Willson et al. (2007) did not make such assumption of common trajectories for all ages, the long-term panel data they used covered a relatively small sample of older adults aged 46-75 at baseline (1,695, 31% of the whole sample), with non-response and attrition over the follow-up period. Uniquely, we were able to evaluate the competing hypotheses of convergence and divergence separately for the different age groups with large sample sizes and no attrition.

A divergence in absolute differences in hospital days over 1988-2007 for men and women aged 50-69 at baseline was observed across education, household income, and occupational class groups. Of these SES indicators, income had the greatest effects on the rate of increase in hospital days. Our results support the idea that education, occupation, and income represent different types of resources and affect health through different pathways: income is more directly related to the material resources available for accessing formal care services, treating health problems, or changing life circumstances to slow down the progression of health problems (House et al., 2005).

The trend toward convergence in absolute SES disparities in hospital days in the group aged 70-79 at baseline supports the AAL hypothesis, which asserts that physiological factors play a larger role in aging than social determinants (Dupre, 2007; Hoffmann, 2008). Benzeval et al. (2011) and Willson et al. (2007) argued that the convergence they observed was artificially caused by mortality selection and/or attrition. In contrast, Rohwer (2016) contended that survival should be viewed as a necessary precondition instead of as a possible source of bias, and that the growth curve models do not estimate the health trajectories conditioned on survival. The pattern-mixture models we used for our sensitivity analysis are fully conditional on survival (Kurland, Johnson, Egleston, & Diehr, 2009). When mortality was taken into account in a series of pattern-mixture models, the changes in relative and absolute SES differences in hospital days found in these models were generally consistent with the results of the MAR models. This suggests that the MAR assumption (i.e., missing hospital days due to death were random after taking into account covariates and hospital days at previous time points) is reasonable. These observations partially confirm the assumption that mortality selection is not the main reason for the convergence in socioeconomic disparities in health at advanced ages (e.g., at ages 75+) (Beckett, 2000; Herd, 2006; House et al., 2005).

There are several possible reasons for the divergence at younger ages and the convergence at older ages in absolute SES differences. Differences in levels of exposure to health risk factors (e.g., health behaviors and psychosocial factors) between socioeconomic groups peak at early and middle ages, and impacts of these health risk factors may fade over the life course (Chandola et al., 2007; House et al., 2005). In addition, the compression of morbidity (i.e., the time between the onset of chronic diseases or disability and the time an individual dies is compressed) at advanced ages may be greater in higher than in lower SES groups (Fries, 1980, 1996). In other words, compared to their counterparts with lower SES, older adults with higher SES may live longer without chronic diseases, disability, or hospitalization; but may experience a steeper terminal decline in health (Fries, 1996). This pattern would lead to a convergence in socioeconomic disparities in health at advanced ages. This trend toward convergence may also be related to the leveling effects of social security and health benefits provided by welfare (Hoffmann, 2008).

Another well-known issue is the need to disentangle birth cohort effects from age effects (House et al., 2005; Lauderdale, 2001; Lynch, 2003; Rohwer, 2016; Willson et al., 2007). Ross & Wu (1996) acknowledged that their findings, using cross-sectional age, of a further divergence in educational differences in self-reported health with increasing age might reflect both age and birth cohort effects. Lauderdale (2001) reported increasing educational differences in survival with age, and that the effect of education was stronger in later than in earlier birth cohorts. Lynch (2003) also showed that ignoring birth cohorts suppressed the widening of socioeconomic gaps in health with age. We took an approach similar to that of Lynch, stratifying our study population by 10-year age groups at baseline (i.e., corresponding to the cohorts born in 1908-1917, 1918-1927, 1928-1937) and estimating the trajectories of hospital days over the follow-up years. It is possible that our approach could not differentiate the true age effect from the period effect. The decline of somatic hospital beds and hospital admissions observed in Finland over 2001-2011 could reflect the improvement of population health, technological advances, and the shift from inpatient care to ambulatory care (Keskimäki, Forssas, Rautiainen, Rasilainen, & Gissler, 2014; Manderbacka, Arffman, & Keskimaki, 2014). Also in the UK, advances in technology, medical treatment, and medical care have been found to reduce the length of hospital stay (Lewis & Edwards, 2015). It is unlikely that the increase in hospital days we observed over 1988-2007 was driven by period effects. However, the advances in medical care made in Finland over our study period may complicate the interpretation of our analyses. Since Finland has a universal health care system, it seems less likely that individuals with higher SES had significantly better access to these advances than those with lower SES. If there was a significant faster increase in access to care among older adults with higher SES, we would observe a convergence across all older ages. This cannot explain the further divergence among those aged 50-69 at baseline.

Remarkable regional variations in health care usage have been observed in Finland due to the differences in population morbidity pattern, medical practices, health care resources and efficiency (Keskimäki et al., 2014). Living in rural areas far away from hospitals (e.g., 40+ km) is found to be associated with fewer days spent in hospital (Zielinski, Borgquist, & Halling, 2013). Finnish individuals who moved from urban to rural areas tend to be older (e.g., after retirement) and with lower education and income (Nivalainen, 2003a, 2003b). However, it is unclear to what extent these processes affect our results because of other urban-rural differences. For instance, the reduction of somatic hospital beds and shift to ambulatory care may be greater in urban than in rural areas, and the medical practices in rural areas may prefer to refer patient to inpatient hospital care more readily than in urban areas. Unfortunately, we do not have information on urban/rural areas to formally test these possibilities; a topic that requires further research.

Our study has some important strengths. First, following recommendations made in previous studies (Dupre, 2007; House et al., 2005; Leopold & Engelhartdt, 2013), our findings were based on 20-year longitudinal data from a large-scale, national representative random sample of older adults. More importantly, we advanced our understanding of changes in relative SES differences in hospital days with increasing age. Since our data came from administrative registers, our findings are not affected by the bias that can arise in panel studies because individuals with low SES or poor health are less likely to participate in studies. We used hospital days to reflect older adults' health status and morbidity. Hospital days is an objective measure that is less prone to measurement error than the subjective measures commonly used in previous studies, such as self-rated health and self-reported disability. It could be argued that hospital days reflect serious health problems only. However, this issue may be less problematic in our study population, as older adults tend to have more serious health conditions than younger adults. We examined educational attainment, household income, and occupational class in order to capture the multi-dimensional character of SES. Particularly for women, household income may be a better indicator of material circumstances than personal income.

We acknowledge that our study also has some limitations. First, the models we used could not describe trajectories over time-varying characteristics. The SES indicators in our study were measured at baseline. Given the ages of our study population, we can assume that their educational attainment was fixed; however, their occupational class and household income may have changed (e.g., after retirement). The occupational class of retirees was based on their previous job status, and remains unchanged. Working-aged older adults may change jobs or become unemployed, but their occupational class is unlikely to change over time. Our data showed that the occupational class remained unchanged for 97% of our study population. Change in household income can be influenced e.g. by retirement and widowhood. We used the age-specific household income tertiles at baseline rather than the updated household income; over 80% of our study population stayed in the same tertile over the follow-up period. Overall, SES thus appears to be relative stable at these older ages.

Second, in Finland, older adults from lower SES groups are more likely to transit into long-term institutional care (Martikainen, Nihtila, & Moustgaard, 2008). We did not exclude institutionalized older adults from this study; instead we coded their hospital days as zero if they did not receive hospital care after they were institutionalized. Therefore, assuming that long-term care substitutes for the care given in hospitals, the hospital days and the rate of increase in hospital days may be downward biased among older adults; in particular among those with lower SES compared to those with higher SES. However, of our study population, only 1200 men (2.0%) and 3470 women (4.4%) had ever been institutionalized, and in 39% of the years that they were institutionalized they also received hospital care. Hence the possibly downward bias in hospital days and rate of increase in hospital days in the lower SES groups due to institutionalization is unlikely to substantially affect our results.

Third, because we were using registry data, we were unable to provide insights into the behavioral mechanisms and the interplay between behavioral risk factors and SES over the life course that could affect health in later life. Thus, future research using panel data with multiple repeated measures on health and related risk factors, and with long-term follow-up to track the health of the older population to advanced ages, is needed to fully explain changes in socioeconomic disparities in late life with increasing age. Moreover, to better explain the convergence in absolute SES differences in health at advanced ages, additional research that investigates the roles of welfare state policies and compression of morbidity is required.

Overall, our findings suggest that the divergence and the convergence in socioeconomic disparities in health at older ages may not be mutually exclusive; as they may depend on the measure of health disparities used and the ages of the populations studied. This implies that more efforts are needed to tackle socioeconomic differences in health in later life, including among the oldest old. A particular focus should be on early old age; a stage of life when absolute SES differentials are still diverging.

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Table 1. Baseline socio-demographic characteristics and mean hospital days in 1988-2007

	Men		**Women**	
	N (%)	Hospital days	N (%)	Hospital days
Total	59586		78067	
Baseline (1988)				
Age (years)				
50-59	27506 (46.2)	2.39	29367 (37.6)	2.18
60-69	20600 (34.6)	5.06	27915 (35.8)	3.85
70-79	11480 (19.3)	11.08	20785 (26.6)	10.69
Native language				
Finnish	54852 (92.1)	5.04	72323 (92.6)	5.07
Swedish/other	4734 (7.9)	4.40	5744 (7.4)	4.77
Region of residence				
Southern	26676 (44.8)	4.78	36335 (46.5)	4.98
Northern	16750 (28.1)	4.58	21653 (27.7)	5.03
Eastern	9186 (15.4)	5.72	11828 (15.2)	5.27
Western	6974 (11.7)	5.79	8251 (10.6)	5.03
Education				
Basic education	43898 (73.7)	5.43	60417 (77.4)	5.51
Beyond basic education	15688 (26.3)	3.75	17650 (22.6)	3.46
Household income				
Low	19899 (33.4)	6.08	26306 (33.7)	5.92
Middle	19822 (33.3)	4.80	25753 (33.0)	4.58
High	19865 (33.3)	4.08	26008 (33.3)	4.62
Occupational class				

Manual, non-specialized/unknown	10351 (17.4)	4.90	19301 (24.7)	4.56
Manual, specialized	18155 (30.5)	5.53	14139 (18.1)	5.68
White collar	15052 (25.3)	3.93	26852 (34.4)	4.05
Other	16028 (26.9)	5.41	17775 (22.8)	6.57
Year				
1988	59586 (100.0)	4.99	78067 (100.0)	5.04
1989	58475 (98.1)	5.26	77088 (98.8)	5.50
1990	56773 (95.3)	5.67	75858 (97.2)	5.98
1991	54967 (92.3)	5.75	74537 (95.5)	6.38
1992	53307 (89.5)	5.96	73120 (93.7)	6.80
1993	51510 (86.5)	6.16	71604 (91.7)	7.36
1994	49761 (83.5)	6.69	69905 (89.5)	7.89
1995	48009 (80.6)	7.01	68238 (87.4)	8.56
1996	46210 (77.6)	7.65	66378 (85.0)	9.36
1997	44421 (74.6)	7.84	64586 (82.7)	9.83
1998	42501 (71.3)	7.93	62615 (80.2)	10.34
1999	40643 (68.2)	8.35	60654 (77.7)	10.89
2000	38773 (65.1)	8.54	58578 (75.0)	11.42
2001	37040 (62.2)	9.02	56353 (72.2)	11.87
2002	35267 (59.2)	9.44	54230 (69.5)	12.12
2003	33469 (56.2)	9.59	52033 (66.7)	12.32
2004	31777 (53.3)	9.58	49770 (63.8)	11.98
2005	30174 (50.6)	9.93	47656 (61.0)	12.12
2006	28573 (48.0)	10.35	45580 (58.4)	12.03
2007	27022 (45.4)	10.05	43503 (55.7)	11.66

Table 2. SES and trajectory of hospital days (relative difference), stratified by baseline age groups

	Men		Women	
	Intercept	**Slope**	**Intercept**	**Slope**
	IRR (95% CI)	IRR (95% CI)	IRR (95% CI)	IRR (95% CI)
Age at baseline				
50-59 years				
Unconditional estimates	2.24 (2.11, 2.37)***	1.06 (1.06, 1.06)***	2.02 (1.90, 2.16)***	1.06 (1.05, 1.06)***
Conditional estimates				
Education[a]				
Beyond basic	0.75 (0.66, 0.85)***	1.01 (1.00, 1.02)	0.72 (0.63, 0.82)***	1.01 (1.00, 1.02)
Household income[b]				
Middle	0.62 (0.55, 0.71)***	1.01 (1.00, 1.02)	0.55 (0.48, 0.63)***	1.01 (1.00, 1.02)*
High	0.43 (0.38, 0.49)***	1.02 (1.01, 1.03)**	0.44 (0.38, 0.52)***	1.01 (1.00, 1.02)
Occupational class[c]				
Manual, specialized	1.01 (0.85, 1.19)	0.99 (0.98, 1.00)	1.22 (1.01, 1.47)*	1.00 (0.98, 1.01)
White collar	0.64 (0.54, 0.75)***	1.00 (0.99, 1.01)	0.83 (0.71, 0.97)*	0.99 (0.98, 1.01)
Other	0.87 (0.74, 1.03)	1.00 (0.99, 1.01)	1.35 (1.09, 1.67)**	0.99 (0.97, 1.00)
60-69 years				
Unconditional estimates	5.08 (4.83, 5.35)***	1.07 (1.06, 1.07)***	3.95 (3.76, 4.15)***	1.09 (1.09, 1.09)***
Conditional estimates				
Education[a]				
Beyond basic	0.88 (0.77, 1.00)	1.00 (0.99, 1.01)	0.74 (0.65, 0.84)***	1.01 (1.00, 1.02)
Household income[b]				

Middle	0.77 (0.69, 0.87)***	1.01 (1.00, 1.02)*	0.80 (0.72, 0.90)***	1.01 (1.00, 1.02)
High	0.62 (0.55, 0.71)***	1.01 (1.00, 1.02)*	0.73 (0.65, 0.83)***	1.01 (1.00, 1.02)
Occupational class[c]				
Manual, specialized	1.04 (0.96, 1.20)	0.99 (0.98, 1.01)	1.25 (1.08, 1.45)**	0.99 (0.98, 1.00)
White collar	0.88 (0.75, 1.04)	0.99 (0.98, 1.01)	0.89 (0.78, 1.02)	1.00 (0.99, 1.01)
Other	0.96 (0.83, 1.11)	1.00 (0.98, 1.01)	1.23 (1.08, 1.41)**	0.99 (0.98, 1.00)*
70-79 years				
Unconditional estimates	11.73 (11.11, 12.39)***	1.07 (1.06, 1.07)***	12.33 (11.81, 12.88)***	1.08 (1.07, 1.08)***
Conditional estimates				
Education[a]				
Beyond basic	0.79 (0.69, 0.91)**	1.01 (0.99, 1.03)	0.78 (0.69, 0.89)***	1.01 (1.00, 1.02)
Household income[b]				
Middle	0.89 (0.78, 1.02)	1.00 (0.99, 1.02)	0.86 (0.78, 0.96)**	1.01 (1.00, 1.02)
High	0.88 (0.77, 1.00)*	1.01 (0.99, 1.02)	0.86 (0.77, 0.95)**	1.00 (0.99, 1.01)
Occupational class[c]				
Manual, specialized	1.02 (0.85, 1.22)	0.99 (0.97, 1.01)	0.83 (0.72, 0.95)**	1.02 (1.00, 1.03)*
White collar	0.83 (0.68, 1.02)	1.00 (0.97, 1.02)	0.83 (0.72, 0.95)**	1.01 (1.00, 1.03)*
Other	0.91 (0.76, 1.09)	1.01 (0.98, 1.03)	0.83 (0.73, 0.95)**	1.02 (1.00, 1.03)*

IRR: Incidence rate ratio; *** p<0.001, ** p<0.01, * p<0.05

Reference categories: [a]basic education, [b]low household income tertile, [c]non-specialized manual class or specialization unknown

Conditional models adjusted for native language and region of residence; all models were fitted separately for education, household income, and occupational class

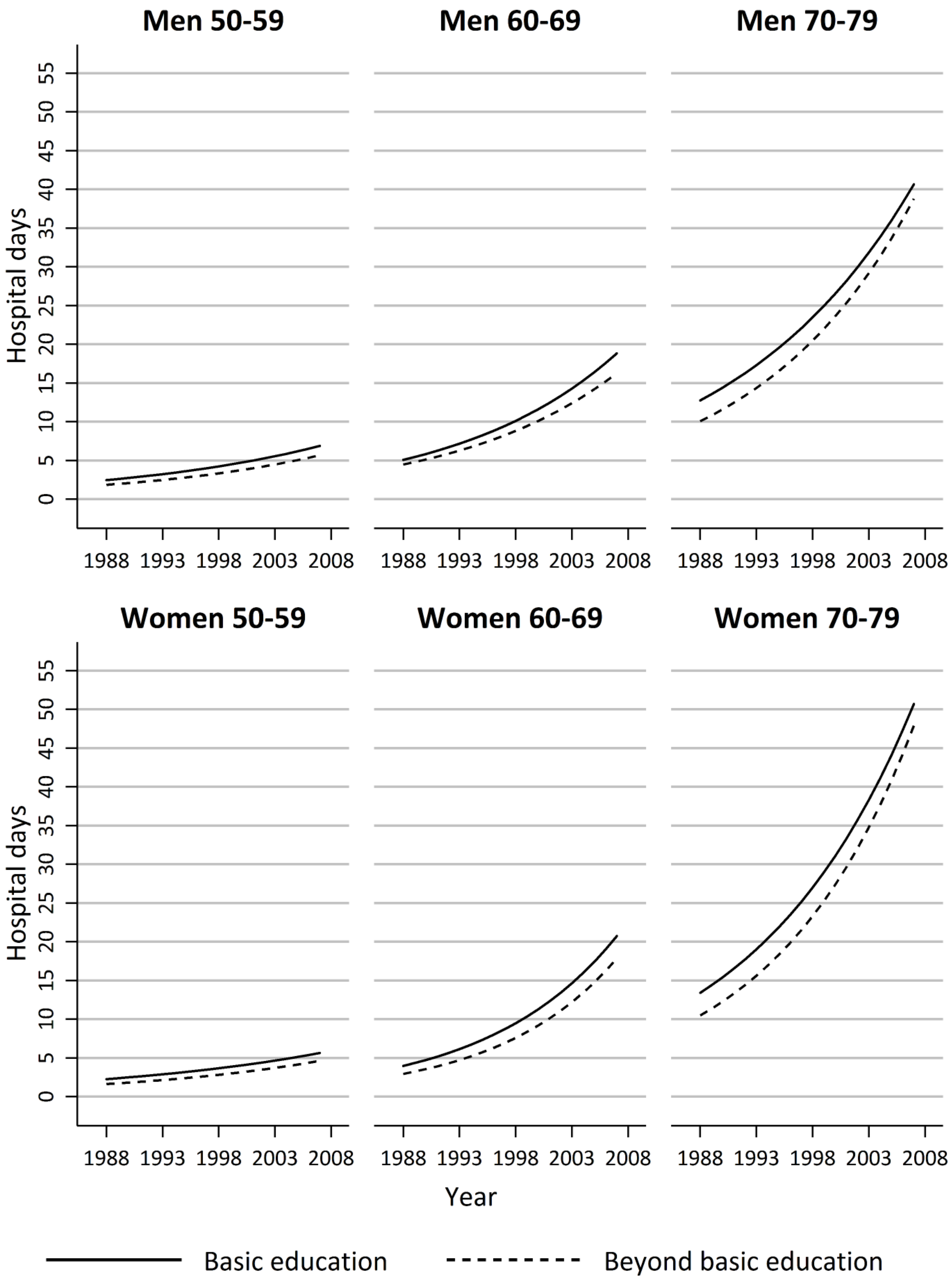


Figure 1. Educational attainment and trajectories of hospital days in 1988-2007 (absolute difference), by sex and age groups at baseline (in 1988)

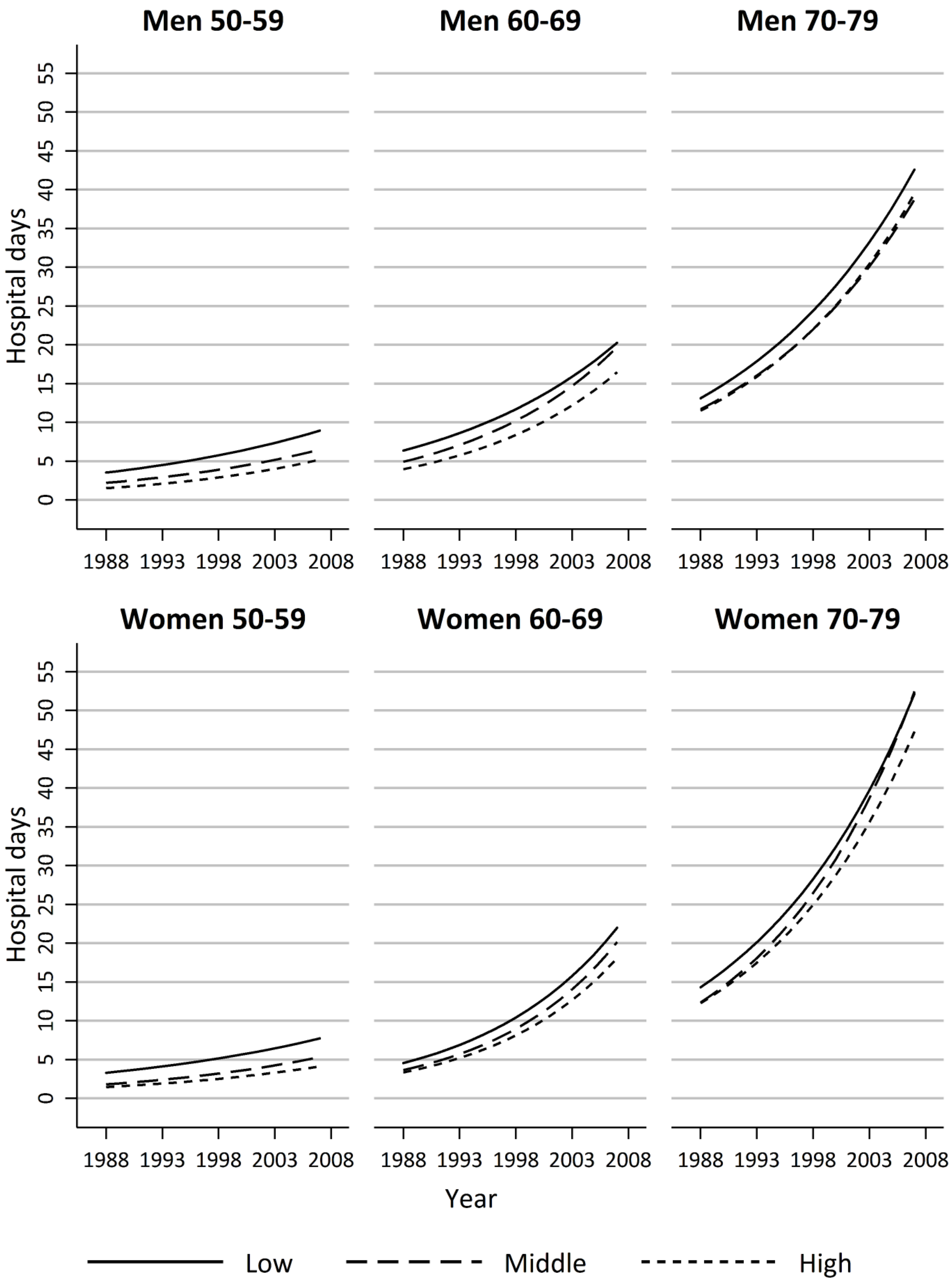


Figure 2. Household income and trajectories of hospital days in 1988-2007 (absolute difference), by sex and age groups at baseline (in 1988)

Supplementary Materials

Section 1. Supplementary Methods

1.1. Model comparison

The data of the over-dispersed hospital days with a preponderance of zeros can be handled by using the negative binomial (NB) model and two zero-altered models: the zero-inflated Poisson (ZIP) model and the zero-inflated negative binomial (ZINB) model (Hilbe, 2007; Ridout, Demetrio, & Hinde, 1998; Zaninotto & Falaschetti, 2011). Unlike the Poisson distribution which assumes that the mean of the count response equals to its variance, the NB regression introduces an error term to account for the over-dispersion (Hilbe, 2007; Zaninotto & Falaschetti, 2011). The error term follows a gamma distribution with a mean of 1 and a variance of α^2 (α is also known as the dispersion parameter). For both the ZIP and ZINB models, the zeros generated from two sources: one source is that a given individual cannot be assumed to have counts other than zero (zero-inflated part); the other source is that the zeros are generated following a Poisson or a negative binomial distribution (count part) (Hilbe, 2007; Zaninotto & Falaschetti, 2011).

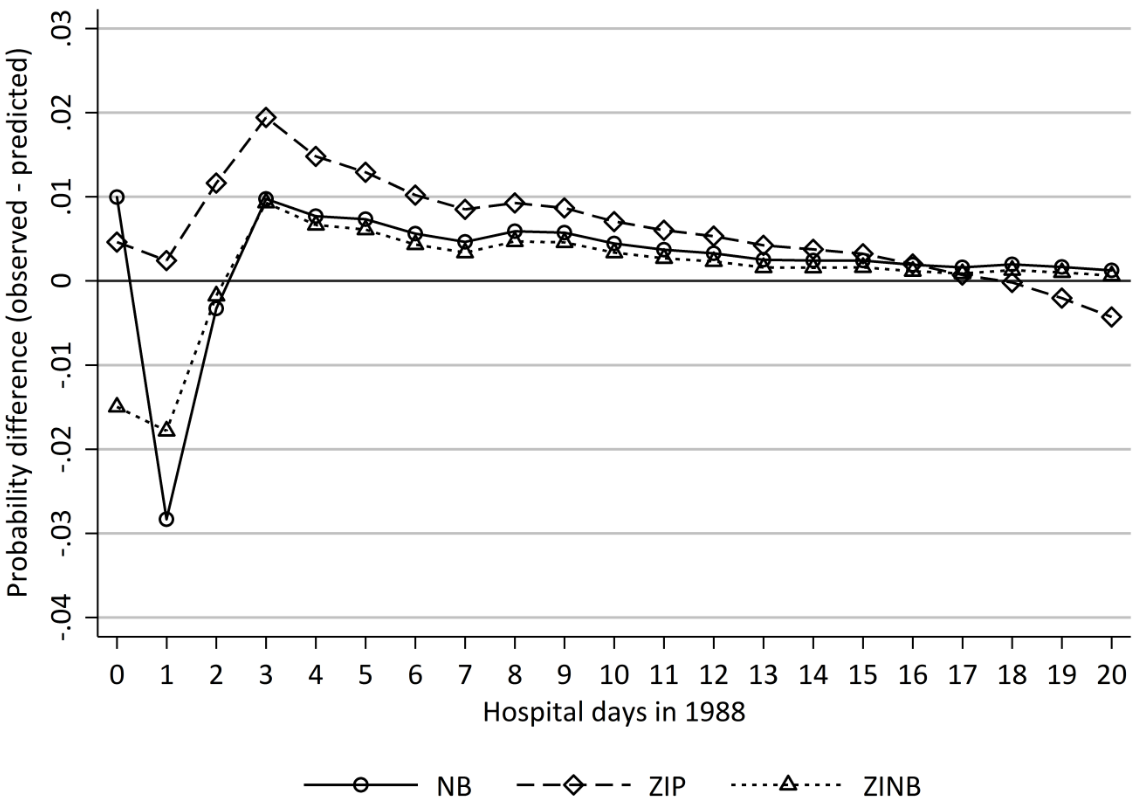
We fitted the 20-year trajectories of hospital days between 1988 and 2007 using the unconditional NB, ZIP and ZINB models in Mplus 7 (Muthén & Muthén, 1998-2015). For the NB model, the trajectories of hospital days are described by two key variables: the intercept that represents the hospital days at baseline (i.e., 1988); and the slope that represents the annual rate of increase in hospital days over the follow-up years 1989-2007. For the ZIP and ZINB models, additional intercept and slope for the zero-inflated part are included. The variance of the intercept, the variance of the slope, and the covariance between the intercept and slope were fixed to zero. All models were estimated using the maximum likelihood estimation with robust standard errors.

Supplementary Table 1 compares the model fit statistics of the unconditional NB, ZIP and ZINB models. Both the Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) were in favor of the NB and ZINB model over the ZIP model, while AIC and BIC were slightly lower in the ZINB model than the NB model. The discrepancy between the observed and predicted probability of hospital days at each year in 1988-2007 was further checked. The largest discrepancy occurred at 1988 (see Supplementary Figure 1). The probability differences were highly similar between the NB and ZINB models for the count of 2 and higher hospital days. The NB model over-estimated the probability of zero hospital day but under-estimated the probability of one hospital day; while ZINB under-estimated both zero and one hospital day. The ZINB model, therefore, did not outperform the NB model fitting our data. In addition, since the NB model is more parsimonious than the ZINB model, the NB model was selected and used in this study.

Supplementary Table 1. Model fit statistics of unconditional latent growth curve NB, ZIP and ZINB models

Model fit statistics	NB	ZIP	ZINB
Number of free parameters	22	4	24
Log-likelihood	-3580396	-15151637	-3570016
Scaling correction factor for maximum likelihood with robust standard error	1.42	237.16	1.80
AIC	7160836	30303281	7140081
BIC	7161052	30303321	7140317
Sample-size adjusted BIC	7160982	30303308	7140241

AIC: Akaike's Information Criterion; BIC: Bayesian Information Criterion



Supplementary Figure 1. Probability difference (observed – predicted) of hospital days in 1988 fitted by NB, ZIP and ZINB

1.2. Pattern-mixture models

Mplus handles missing data using full information maximum likelihood (FIML), a statistical estimation technique that is valid under the assumption of missing at random (MAR, i.e., missingness depends on covariates and the outcome variable observed at previous time points) (Muthén, Asparouhov, Hunter, & Leuchter, 2011; Muthén & Muthén, 1998-2015). This approach does not differentiate the missing due to drop-out and the missing due to death (Dufouil, Brayne, & Clayton, 2004). It implies that the trajectories of hospital days are estimated as if no individual died (the observed information from alive individuals is used to "impute" the missing information for deceased individuals) (Dufouil et al., 2004; Kurland, Johnson, Egleston, & Diehr, 2009).

If the MAR assumption does not hold, missing not at random (MNAR) models should be used to perform a sensitivity analysis (Muthén et al., 2011; Newsom, 2015). Different approaches have been proposed to specify the joint distribution of the response Y_i and the indicator of missing data R_i (Demirtas & Schafer, 2003; Enders, 2011; Little, 2009; B. Muthén et al., 2011; Verbeke, Lesaffre, & Spiessens, 2001). The joint distribution $f(Y_i, R_i)$ is specified in the pattern-mixture model as:

$$f(Y_i, R_i) = f(R_i)f(Y_i|R_i) \tag{2}$$

Where $f(R_i)$ is the marginal distribution of R_i, $f(Y_i|R_i)$ is the conditional distribution of Y_i given R_i.

As argued by (Little, 2009), for the case of missing due to death, it appears to be more meaningful to consider the conditional distribution of Y_i given $R_i = 1$ (survivors) rather than the marginal distribution of Y_i. Latent growth curve modeling, an approach to analyze repeated measures data with the aim of describing the developmental trajectory, has already been extended to count data and to handle MNAR (Hox, 2013; Muthén & Muthén, 1998-2015). Therefore we fitted pattern-mixture models within the framework of latent growth curve modeling as the sensitivity analysis supplemented to the MAR models, in which both the intercept and the slope were modeled as a function of death indicators (Muthén, Asparouhov, Hunter, & Leuchter, 2011; Muthén & Muthén, 1998-2015; Newsom, 2015). In Mplus, the death indicators were coded as following: the value of one was assigned to the time point after the last time point an individual was observed, whereas the value of zero was assigned to all other time points (Muthén & Muthén, 1998-2015). The pattern-mixture models should be used to serve the purpose of sensitivity analysis complemented to the MAR models because the pattern-mixture models, similar as the MAR models, also make assumptions on the mechanisms of missingness that cannot be tested (Muthén et al., 2011; Newsom, 2015).

Section 2. Supplementary Tables and Figures

Supplementary Table 2. SES and trajectory of hospital days (relative difference) in the pooled sample of men and women, stratified by 10-year age groups at baseline

	Intercept (95% CI)	**Slope** (95% CI)
Age at baseline		
50-59 years		
Education		
Basic	Ref	Ref
Beyond basic	0.73 (0.67, 0.80)	1.01 (1.00, 1.01)
Household income*		
Low	Ref	Ref
Middle	0.59 (0.53, 0.65)	1.01 (1.00, 1.02)
High	0.43 (0.39, 0.48)	1.01 (1.01, 1.02)
Occupational class§		
Manual, non-specialized/ specialization unknown	Ref	Ref
Manual, specialized	1.13 (0.99, 1.28)	0.99 (0.98, 1.00)
White collar	0.74 (0.66, 0.83)	1.00 (0.99, 1.01)
Other	1.09 (0.95, 1.24)	1.00 (0.99, 1.00)
60-69 years		
Education		
Basic	Ref	Ref
Beyond basic	0.80 (0.73, 0.88)	1.00 (1.00, 1.01)
Household income*		
Low	Ref	Ref
Middle	0.79 (0.73, 0.86)	1.01 (1.00, 1.01)
High	0.68 (0.63, 0.75)	1.01 (1.00, 1.02)
Occupational class§		
Manual, non-specialized/ specialization unknown	Ref	Ref
Manual, specialized	1.16 (1.05, 1.29)	0.99 (0.98, 1.00)
White collar	0.89 (0.80, 0.99)	1.00 (0.99, 1.00)
Other	1.11 (1.01, 1.23)	0.99 (0.98, 1.00)
70-79 years		
Education		
Basic	Ref	Ref
Beyond basic	0.78 (0.71, 0.86)	1.01 (1.00, 1.02)
Household income*		
Low	Ref	Ref
Middle	0.87 (0.80, 0.95)	1.01 (1.00, 1.01)
High	0.86 (0.80, 0.94)	1.00 (1.00, 1.01)
Occupational class§		
Manual, non-specialized/ specialization unknown	Ref	Ref
Manual, specialized	0.88 (0.79, 0.99)	1.01 (1.00, 1.02)
White collar	0.82 (0.73, 0.92)	1.01 (1.00, 1.02)
Other	0.85 (0.76, 0.94)	1.01 (1.00, 1.02)

* Categorized by sex- and age-group-specific tertiles

§ Other occupational class includes farmers, self-employed, students, other or unknown

Ref: reference category

Adjusted for sex, native language (Finnish, and Swedish or other) and region of residence (southern, northern, east, and western Finland); all models were fitted separately for education, household combined consumption income, and occupational class

Supplementary Table 3. SES and trajectory of annual total number of hospitalization (relative difference), stratified by baseline age groups

	Men				Women			
	Intercept		Slope		Intercept		Slope	
	IRR (95% CI)	p value	IRR (95% CI)	p value	IRR (95% CI)	p value	IRR (95% CI)	p value
Age at baseline								
50-59 years								
Unconditional estimates	0.26 (0.25, 0.26)	<0.001	1.05 (1.05, 1.06)	<0.001	0.21 (0.21, 0.22)	<0.001	1.05 (1.05, 1.06)	<0.001
Conditional estimates								
Education[a]								
Beyond basic	0.83 (0.78, 0.87)	<0.001	1.00 (1.00, 1.01)	0.42	0.86 (0.81, 0.91)	<0.001	1.00 (1.00, 1.00)	0.93
Household income[b]								
Middle	0.82 (0.77, 0.87)	<0.001	1.00 (1.00, 1.01)	0.13	0.80 (0.75, 0.85)	<0.001	1.00 (1.00, 1.01)	0.38
High	0.69 (0.65, 0.73)	<0.001	1.00 (1.00, 1.01)	0.13	0.74 (0.69, 0.79)	<0.001	1.00 (0.99, 1.00)	0.96
Occupational class[c]								
Manual, specialized	1.01 (0.94, 1.08)	0.81	1.00 (0.99, 1.00)	0.11	1.10 (1.01, 1.20)	0.03	1.00 (0.99, 1.01)	0.81
White collar	0.79 (0.74, 0.85)	<0.001	1.00 (0.99, 1.00)	0.58	0.88 (0.83, 0.94)	<0.001	1.00 (1.00, 1.01)	0.60
Other	0.94 (0.87, 1.02)	0.12	1.00 (0.99, 1.01)	0.81	1.08 (1.00, 1.17)	0.05	1.00 (0.99, 1.00)	0.67
60-69 years								
Unconditional estimates	0.45 (0.44, 0.46)	<0.001	1.06 (1.05, 1.06)	<0.001	0.34 (0.33, 0.35)	<0.001	1.06 (1.06, 1.07)	<0.001
Conditional estimates								
Education[a]								
Beyond basic	0.87 (0.82, 0.93)	0.06	1.00 (1.00, 1.01)	0.82	0.85 (0.81, 0.91)	<0.001	1.00 (1.00, 1.01)	0.27
Household income[b]								
Middle	0.88 (0.83, 0.93)	<0.001	1.00 (1.00, 1.01)	0.24	0.85 (0.81, 0.90)	<0.001	1.01 (1.00, 1.01)	<0.01
High	0.79 (0.74, 0.84)	<0.001	1.01 (1.00, 1.01)	0.02	0.82 (0.77, 0.87)	<0.001	1.00 (1.00, 1.01)	0.22
Occupational class[c]								
Manual, specialized	1.11 (1.03, 1.20)	<0.01	0.99 (0.98, 1.00)	0.01	1.13 (1.06, 1.21)	<0.001	1.00 (0.99, 1.00)	0.19
White collar	0.90 (0.83, 0.97)	0.10	1.00 (0.99, 1.01)	0.69	0.99 (0.93, 1.05)	0.76	0.99 (0.99, 1.00)	0.01
Other	1.00 (0.93, 1.08)	0.95	1.00 (0.99, 1.01)	0.87	1.23 (1.15, 1.31)	<0.001	0.99 (0.99, 1.00)	<0.001
70-79 years								
Unconditional estimates	0.74 (0.72, 0.76)	<0.001	1.05 (1.05, 1.05)	<0.001	0.63 (0.62, 0.64)	<0.001	1.05 (1.05, 1.05)	<0.001
Conditional estimates								
Education[a]								
Beyond basic	0.82 (0.77, 0.88)	<0.01	1.01 (1.00, 1.02)	0.01	0.85 (0.80, 0.90)	<0.001	1.01 (1.00, 1.01)	0.03
Household income[b]								
Middle	0.91 (0.85, 0.97)	<0.01	1.00 (1.00, 1.01)	0.22	0.87 (0.83, 0.92)	<0.001	1.01 (1.00, 1.01)	<0.001
High	0.86 (0.80, 0.92)	<0.001	1.01 (1.00, 1.01)	0.10	0.85 (0.80, 0.89)	<0.001	1.01 (1.00, 1.01)	<0.001
Occupational class[c]								

Manual, specialized	1.07 (0.97, 1.17)	0.16	1.00 (0.99, 1.01)	0.46	1.03 (0.97, 1.10)	0.31	1.00 (1.00, 1.01)	0.60
White collar	0.94 (0.86, 1.04)	0.24	1.00 (0.99, 1.01)	0.89	0.98 (0.92, 1.05)	0.63	1.00 (0.99, 1.01)	0.93
Other	1.02 (0.94, 1.12)	0.59	1.01 (0.99, 1.01)	0.95	1.08 (1.01, 1.14)	0.02	1.00 (0.99, 1.00)	0.49

IRR: Incidence rate ratio

Reference categories: [a]basic education, [b]low household income tertile, [c]non-specialized manual class or specialization unknown

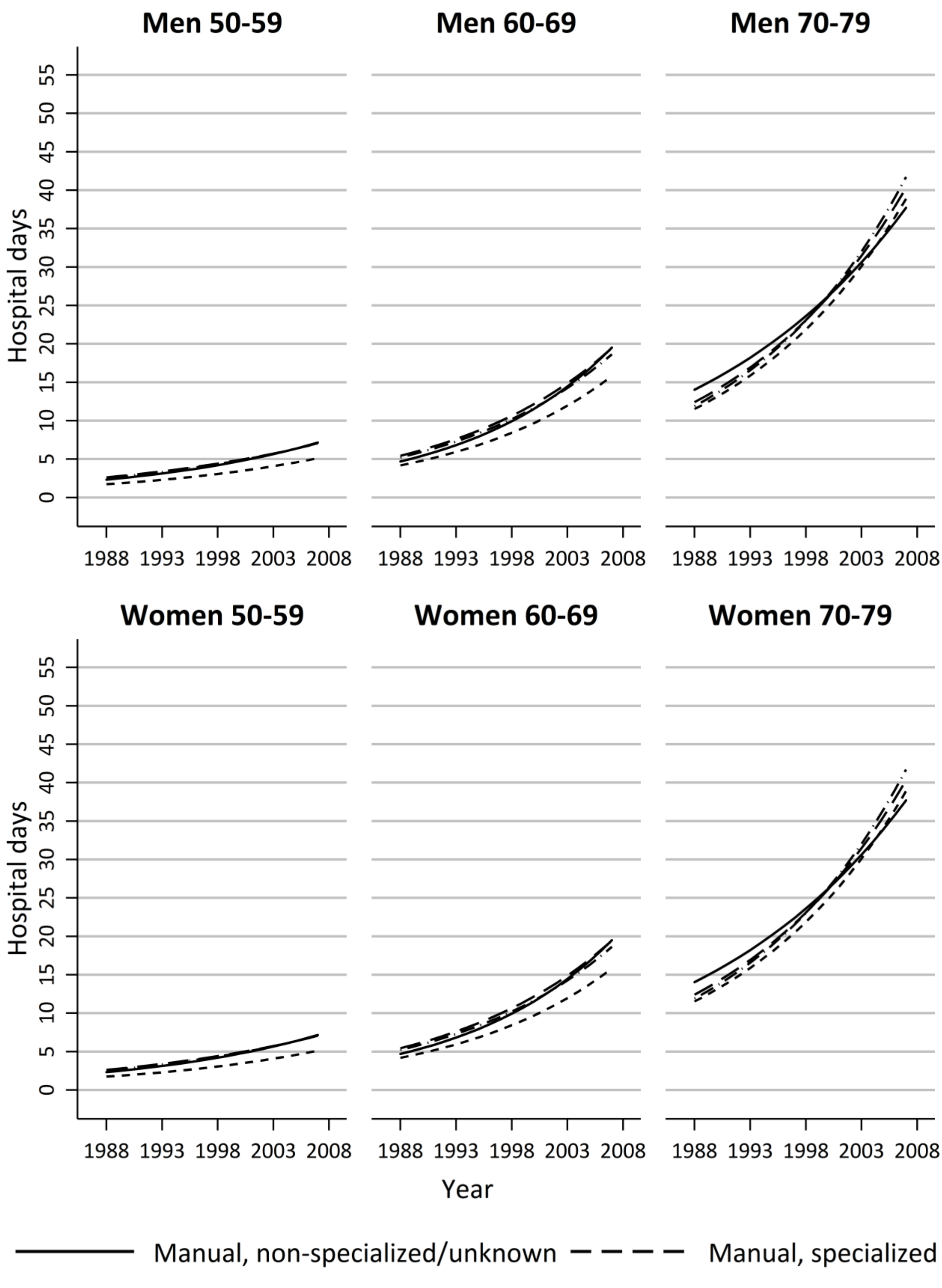
Conditional models adjusted for native language and region of residence; all models were fitted separately for education, household income, and occupational class

Supplementary Table 4. SES and trajectory of hospital days (relative difference) in men and women fitted by pattern-mixture model, stratified by 10-year age groups at baseline

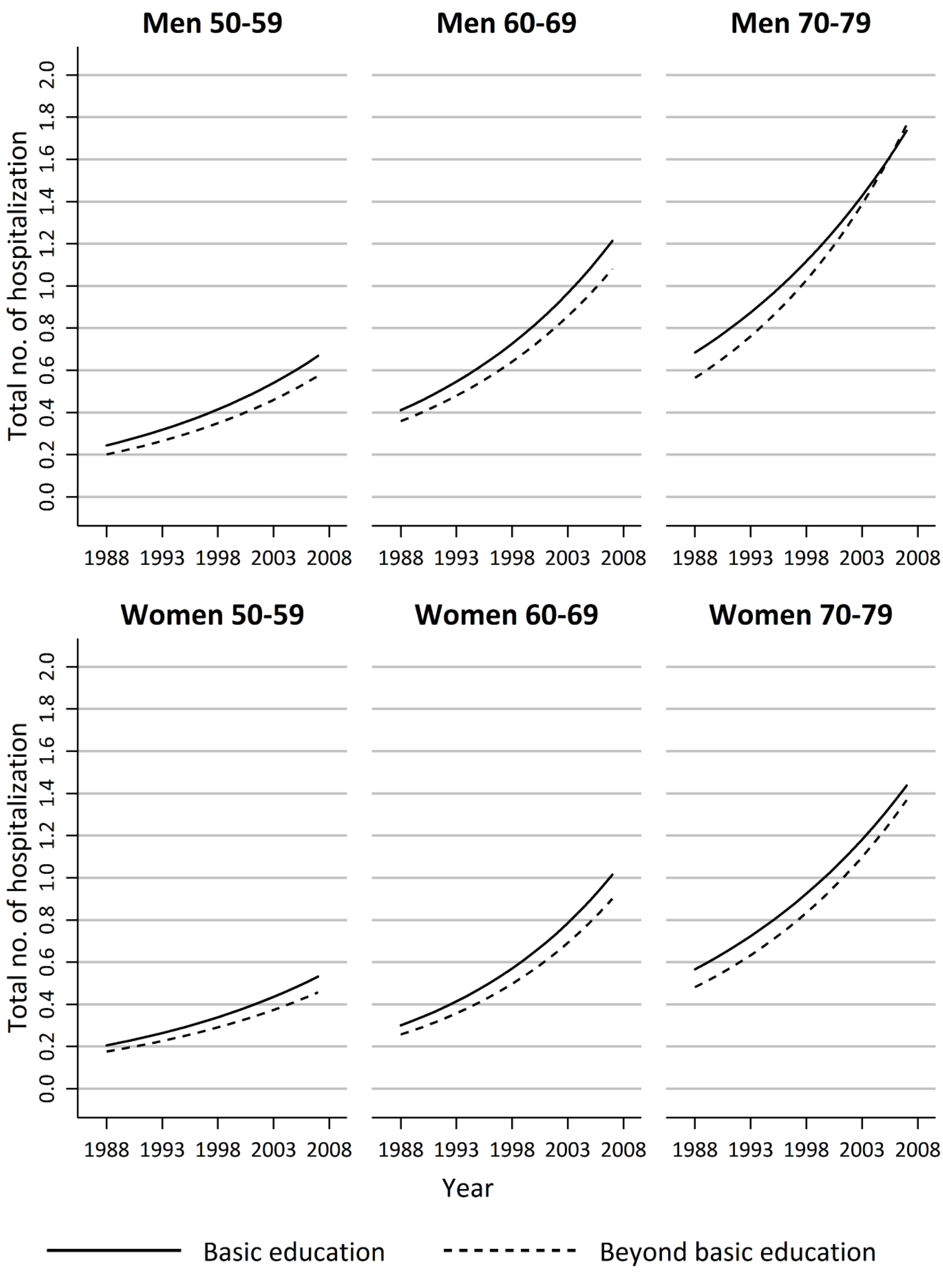
	Men				Women			
	Intercept		Slope		Intercept		Slope	
	IRR (95% CI)	p value	IRR (95% CI)	p value	IRR (95% CI)	p value	IRR (95% CI)	p value
Age at baseline								
50-59 years								
Education[a]								
Beyond basic	0.91 (0.81, 1.03)	0.13	1.00 (0.99, 1.01)	0.63	0.81 (0.72, 0.91)	<0.001	1.00 (0.99, 1.01)	0.78
Household income[b]								
Middle	0.76 (0.67, 0.86)	<0.001	1.00 (0.99, 1.01)	0.51	0.64 (0.55, 0.74)	<0.001	1.00 (0.99, 1.01)	0.56
High	0.65 (0.58, 0.73)	<0.001	1.00 (0.99, 1.01)	0.92	0.53 (0.46, 0.62)	<0.001	1.00 (0.99, 1.01)	0.78
Occupational class[c]								
Manual, specialized	0.99 (0.85, 1.15)	0.89	0.99 (0.98, 1.01)	0.34	1.06 (0.91, 1.22)	0.50	1.01 (0.99, 1.02)	0.44
White collar	0.81 (0.68, 0.96)	0.02	0.99 (0.98, 1.01)	0.33	0.88 (0.77, 1.00)	0.05	1.00 (0.98, 1.01)	0.41
Other	0.95 (0.80, 1.13)	0.56	1.00 (0.99, 1.01)	0.90	1.32 (1.05, 1.66)	0.02	0.99 (0.98, 1.01)	0.26
60-69 years								
Education[a]								
Beyond basic	1.04 (0.92, 1.17)	0.56	1.00 (0.99, 1.00)	0.32	0.86 (0.78, 0.95)	<0.01	1.00 (0.99, 1.01)	0.64
Household income[b]								
Middle	0.87 (0.78, 0.98)	0.02	1.00 (0.99, 1.01)	0.69	0.86 (0.78, 0.95)	<0.01	1.00 (1.00, 1.01)	0.40
High	0.78 (0.68, 0.90)	<0.001	1.00 (0.99, 1.01)	0.65	0.85 (0.76, 0.94)	<0.01	1.00 (0.99, 1.01)	0.97
Occupational class[c]								
Manual, specialized	1.05 (0.92, 1.19)	0.48	0.99 (0.98, 1.01)	0.37	1.11 (0.98, 1.24)	0.09	1.00 (0.99, 1.01)	0.66
White collar	1.08 (0.91, 1.28)	0.36	0.99 (0.97, 1.00)	0.05	1.02 (0.92, 1.13)	0.72	0.99 (0.98, 1.00)	0.02
Other	1.09 (0.96, 1.24)	0.19	0.99 (0.98, 1.00)	0.21	1.24 (1.10, 1.39)	<0.001	0.99 (0.98, 1.00)	0.02
70-79 years								
Education[a]								
Beyond basic	0.80 (0.70, 0.92)	<0.01	1.01 (1.00, 1.03)	0.13	0.84 (0.74, 0.95)	<0.01	1.01 (1.00, 1.02)	0.28
Household income[b]								
Middle	0.97 (0.84, 1.11)	0.62	0.99 (0.98, 1.01)	0.51	0.91 (0.82, 1.01)	0.09	1.00 (0.99, 1.01)	0.81
High	0.91 (0.80, 1.05)	0.18	1.00 (0.99, 1.02)	0.92	0.86 (0.78, 0.96)	<0.01	1.01 (0.99, 1.02)	0.32
Occupational class[c]								
Manual, specialized	1.10 (0.91, 1.34)	0.33	0.99 (0.97, 1.01)	0.47	0.86 (0.74, 0.99)	0.04	1.01 (1.00, 1.03)	0.15
White collar	0.91 (0.75, 1.10)	0.35	1.00 (0.97, 1.02)	0.76	0.86 (0.75, 0.99)	0.04	1.01 (1.00, 1.03)	0.10
Other	1.02 (0.85, 1.23)	0.82	1.00 (0.98, 1.03)	0.82	0.91 (0.79, 1.04)	0.16	1.01 (1.00, 1.02)	0.22

IRR: Incidence rate ratio

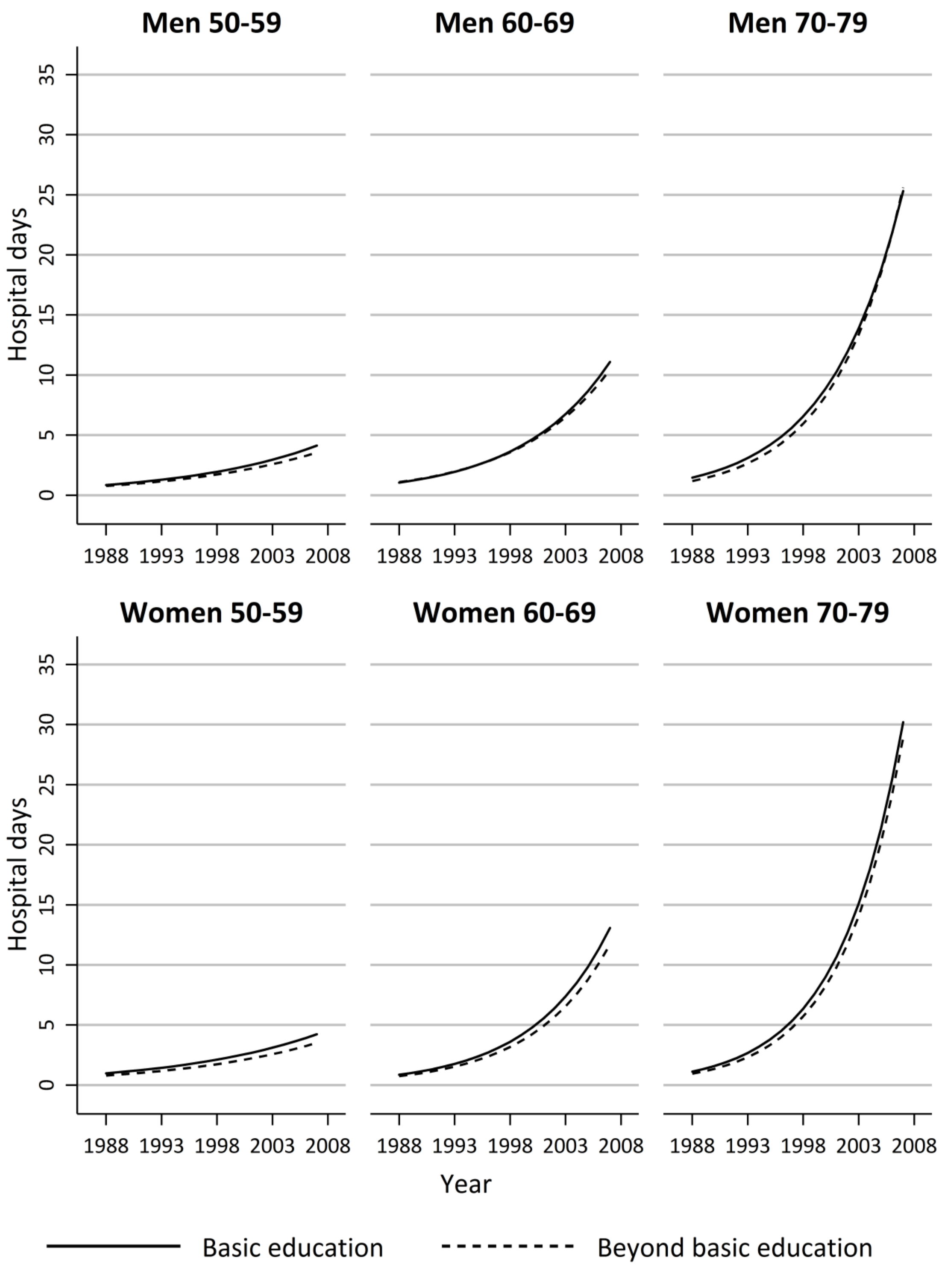
Reference categories: [a]basic education, [b]low household income tertile, [c]non-specialized manual class or specialization unknown
Conditional models adjusted for native language and region of residence; all models were fitted separately for education, household income, and occupational class



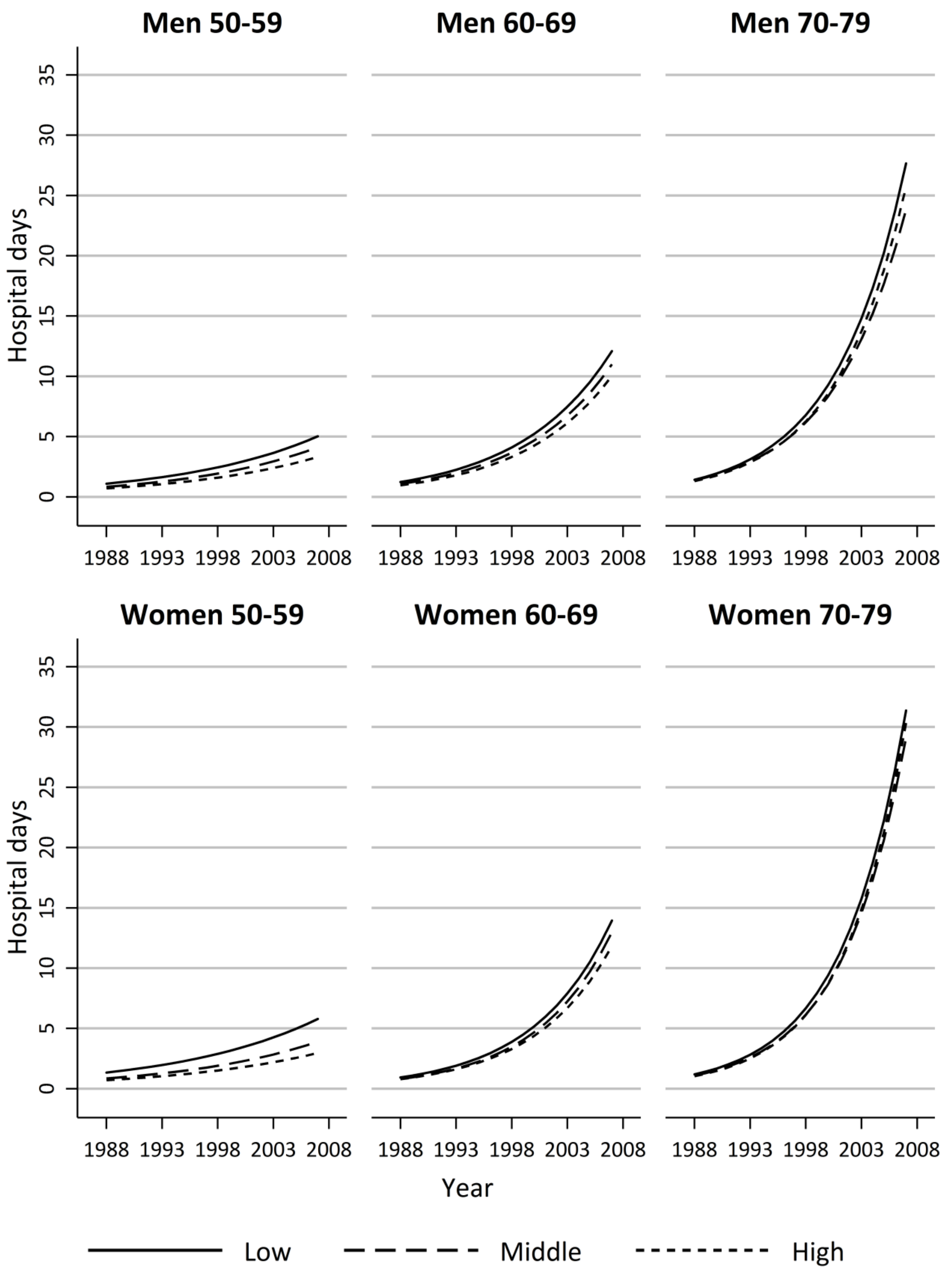
Supplementary Figure 2. Occupational class and trajectories of hospital days in 1988-2007 (absolute difference), by sex and 10-year age groups at baseline (in 1988)



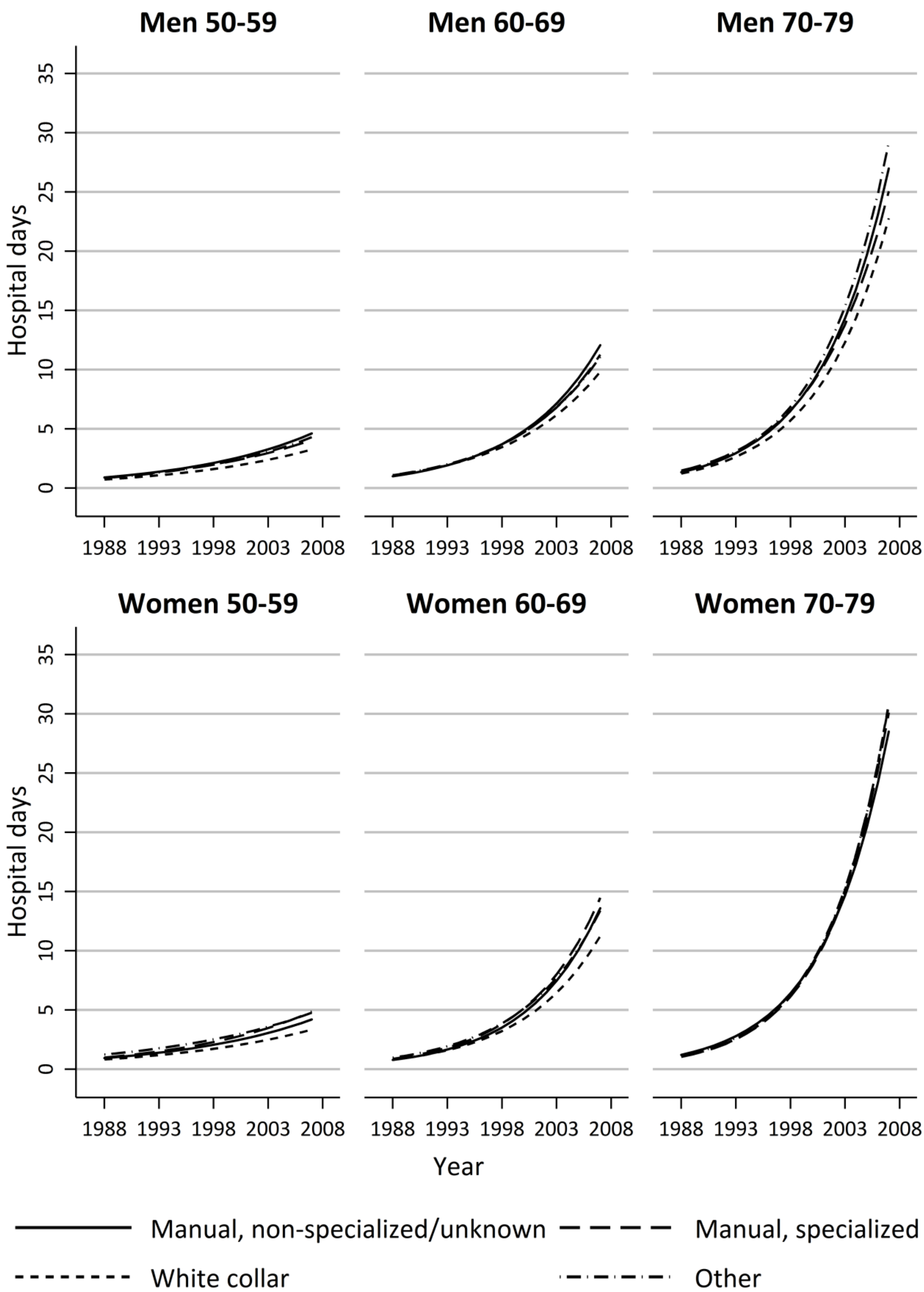
Supplementary Figure 3. Education and trajectories of total number of hospitalization in 1988-2007 (absolute difference), by sex and 10-year age groups at baseline (in 1988)



Supplementary Figure 4. Educational attainment and trajectories of hospital days in 1988-2007 (absolute difference) fitted in pattern-mixture models, by sex and 10-year age groups at baseline (in 1988)



Supplementary Figure 5. Household income and trajectories of hospital days in 1988-2007 (absolute difference) fitted in pattern-mixture models, by sex and 10-year age groups at baseline (in 1988)



Supplementary Figure 6. Occupational class and trajectories of hospital days in 1988-2007 (absolute difference) fitted in pattern-mixture models, by sex and 10-year age groups at baseline (in 1988)

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