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Projecting morbidity in Denmark using the SMILE microsimulation model

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1. Abstract

Three theories dominate research on predicting morbidity patterns, namely *morbidity expansion* (Gruenberg, 2005), *morbidity compression* (Fries, 1980), and *dynamic equilibrium* (Manton, 1982). To examine the morbidity and functioning disability prospects of an aging population, these theories are simulated for the Danish population using the Danish microsimulation model SMILE. To project morbidity and functioning disability, SMILE relies on Danish administrative register data and data from the Survey of Health, Ageing and Retirement in Europe (SHARE[1]). This exercise should aid to a better understanding of the scope of health care and fiscal challenges associated with an aging population. From both the perspective of morbidity and functioning disability, projections results indicate a worsening or a resemblance of the state in 2013 for the seniors in Denmark (aged 50-100), mainly due to changes in the age composition. These results apply even in scenarios where the population is less likely to get in more morbid states (morbidity compression) or less impaired by diseases (dynamic equilibrium) at a given age.

2. Demographic challenges and morbidity patterns

From 2018 to 2040, the Danish population is expected to grow by approximately 0.5 million, corresponding to 9%. The share of the population at retirement age or older (65+) is predicted to increase (19.5% to 24.5%) mainly at the cost of the working age population (age 15-64) that is predicted to decline (64% to 58%). Thus, the share of seniors will increase, and this is primarily due to older seniors. Of the total population, seniors in pre-retirement (50-64) are expected to decline (20% to 16%). However, seniors in early retirement age (65-75) are expected to increase slightly (11.5% to 12.5%) while late retirement age seniors (age 75+) are expected to increase markedly (7% to 12%). This outlook is likely to put extra demand on health care and challenge public finances. From a fiscal perspective, reforms increasing the public pension age partially address the public finance challenge. However, morbidity patterns of the aging working force and the expenditures to health care of the aging retired population will also determine whether current reforms are sufficient.

[1] *This paper uses data from SHARE Waves 1, 2, 3, 4 and 5 (DOIs: 10.6103/SHARE.w1.700, 10.6103/SHARE.w2.700, 10.6103/SHARE.w3.700, 10.6103/SHARE.w4.700, 10.6103/SHARE.w5.700, see Börsch-Supan et al. (2013) for methodological details.*

The concern over an aging population associated with an increased fiscal burden is not new. Over the past two centuries, life expectancy has increased. This long term trend, combined with the baby-boomers from the 60s entering old age, has aged the population across several countries. This trend has raised concerns about increasing health care costs because people in old age are more afflicted by disease relative to young people (Gruenberg, 2005). However, others have noted, that old people may live a less disease afflicted life than earlier. This could reduce health care needs and perhaps also prolong labor market participation (Fries, 1980; Manton, 1982).

The aging population is mostly a result of improved life expectancy over the last two centuries. Since the 1850s, the decline in mortality has mainly come from reductions in childhood mortality and improvements in fighting infectious disease (e.g., pneumonia). Since the 1950s, increases in life expectancy have been mainly due to declines in old-age mortality. The improved mortality for seniors has shifted the morbidity patterns for the elderly population, such that chronic conditions (e.g., cancer and cardiovascular disease) are more prevalent cause of death than infectious diseases. The increased prevalence of chronic diseases has important implications because people saved from death from infectious diseases often live their lives without being affected by the condition whereas people surviving chronic disease often lives with chronic conditions and treatment for extended periods (Crimmins and Beltrán-Sanchéz, 2010). In the late 70s and beginning of the 80s, this shift in morbidity patterns paved the way for three diverging predictions for future morbidity patterns, namely *morbidity expansion*, *morbidity compression,* and *dynamic equilibrium*.

3. Three perspectives on future morbidity

In the late 70s, Gruenberg (2005) observed how successful technological advances significantly reduced death caused by infectious disease. However, he also noted that this also extended the time spend in chronic disease. He coined this "The Failure of Success." Other scholars have referred to this phenomenon as *morbidity expansion* (for example, Crimmins and Beltrán-Sanchéz, 2010).

Fries (1980) argued that another phenomenon might present itself, namely *morbidity compression.* People would be able to postpone the onset of chronic disease, but eventually, they would reach an age where biological limits would result in death after a relatively short period in disease. Since Gruenberg's paper in 1977 and Fries' paper in 1980, the dichotomy between morbidity expansion and morbidity compression became a vehicle for research in morbidity patterns. Also, they inspired a third position.

Manton (1982) theorized a position between morbidity compression and morbidity expansion, which he coined *dynamic equilibrium*. In this scenario, changes in the rate of progression and the severity of chronic disease would keep pace with mortality changes. Thus, as mortality declines, so does the rate of progression and the severity of chronic diseases, hence the notion of dynamic equilibrium. On the one hand, this would result in more disease in the population, but on the other hand, diseases would have less consequence in terms on people's functional ability and in the risk of death associated with diseases.

4. Defining morbidity and functioning disability

Morbidity is multidimensional in the way that there are many types of diseases. Further, people diagnosed with the same disease may be at different stages of the disease, which implies different levels of functioning impairment. Therefore, many different proxies are applied to measure morbidity. Often activities of daily living (ADLs), instrumental activities of daily living (IADLs) or self-reported (chronic) disease are used as measures (see for example Crimmins et al. 2010, Cutler et al., 2013; Beltrán-Sanchéz et al. 2016) but other measures such as biomarkers and performance measures of functioning (e.g., climbing a flight of stairs, walking a specific range) are also present in the literature (Martin et al. 2010; Chatterji et al. 2015).

In this study, projections are evaluated using a morbidity measure and a functioning disability measure. The morbidity measure is a morbidity index derived from using principal component analysis on Danish administrative register data on health while survey responses on ADLs from the SHARE-survey are the basis for the functioning disability index.

The morbidity index comprises hospitalization, doctor visits by type of specialization, and prescription data, including doses. The index is measured for the population aged 15-100. This approach broadly follows Bingley et al. (2014)[2]. Hospitalization comprises the sum of hospital stays for each person within each diagnosis over two years by a 3-digit diagnosis-code. 3-digit diagnoses with less than 100 different individuals are removed to a final of 204 3-digit diagnoses. Prescriptions are aggregated by four-digit ATC code (ATC-4), and the standardized daily dose (DDD) is summed for each diagnosis for each person over two years. All ATC4 with less than 100 different individuals purchasing are removed to get the DDD for 379 ATC4s. Doctor visits by type of specialist are aggregated by 3-digit specialization code, and the fees are summed for each 3-digit specialization for each person over two years. Visits by 3-digit specialization with less than 100 different individuals are removed to get a final of 142 3-digit specializations.

The principal component analysis approach has the advantage of providing a low dimensional representation of data that captures as much information in data as possible (James et al. 2015). Individual-specific score values of the first principal component construct the index by grouping the population into percentiles (i.e., 100 groups), where high values are associated with worse morbidity states. This procedure results in a categorical index that has a broad population coverage, which minimizes the need for imputations and keeps substantial information about differences in morbidity. It arguably includes more of the latent morbidity than more simplistic metrics or indices, and it makes it possible to track even small changes over time. However, the index is less tangible compared to, for example, counting diagnoses or functioning disability prevalence.

There are some limitations to the morbidity index. First, the index is relative. Therefore the projection of an individual's position in the morbidity index should be interpreted as how a person would rank given she lived in 2013 with the same morbidity index. Second, this paper aims to predict latent morbidity rather than predict medicine or other health service utilization of a person. In the future, new medicine or other types of treatments may prove more efficient than current technology. However, the working assumption is that the diseases it tries to remedy are predominantly the same in the future. Thus, the morbidity index enables evaluations of morbidity of projected populations relative to the morbidity distribution scenario in 2013. A final caveat is that

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[2]Bingley et al. (2014) coin it a "health index". While the index indirectly reveals information on health, it does not distinguish between whether there are any differences in health among those who do not have a disease even if this may be the case. Therefore, it is more obvious to treat the index as a morbidity index. For example, imagine two persons that have not engaged with the health system a given year. One exercises regularly, and one does not. Even if diseases afflict neither, the former is likely to be healthier than the latter, but obviously, the index would not catch this.

health care usage rather than health care needs are used to construct the index. Thus, the morbidity index may, in some cases, fail to represent that some people are less likely to attain the necessary health care, although the need is present. For example, it is conventional to observe that men have less health care usage but higher mortality relative to women of a similar age (Bingley, 2014).

The functioning disability measure captures the prevalence of limitations in ADLs. The measure is based on whether respondents in SHARE consider themselves to be “severely limited,” “limited, but not severely” or “not limited” in their ADLs. Compared to the morbidity index, the functioning disability index is more tangible, but it is less sensitive to small changes over time, and all values need to be imputed as data does not exist for the base year in SMILE.

While a relatively precise prediction of latent morbidity may reveal costs related to health services such as medicine, hospitalization and doctor visits, a projection of functioning disability may reveal care expenses but also benefits from treatments of chronic conditions related to an aging population. Benefits may comprise higher labor force participation (for both individuals receiving care and potential informal caretakers)[3] or merely being more able to do whatever a person has reason to value (WHO, 2015). These benefits are essential to take into account in, for example, welfare analysis that assesses cost and benefits concerning treatments of chronic diseases.

5. Microsimulation

The dynamic data-driven microsimulation model SMILE[4] is used to project the three morbidity scenarios. The model also projects demography, household structure, ongoing and highest education, socioeconomic characteristics, pension, transfers, income, taxation, and housing demand. The initial population in 2013 comprises 2.8 million households, which in turn comprises 5.5 million individuals. Deaths, births, and migration are aligned to the official national population projection in standard projections, although this is not the case for deaths in simulations in this study. Further, SMILE provides a detailed description of sub-national moving behavior to identify geographic areas characterized by future negative and positive growth. The model has been documented elsewhere (Hansen et al., 2016; Stephensen, 2015; Rasmussen and Stephensen, 2014; Stephensen, 2013; Hansen et al. 2013). Therefore, the primary concern in this paper is to present the morbidity and functioning disability modeling. The predictive modeling is carried out using the statistical software program R (R Core Team, 2018). In particular, CTREEs are estimated using the partykit package (Horton et al. 2006; Horton and Zeileis, 2015) while cross-validation is carried out using the caret package (Kuhn, 2006).

6. Building predictive models for morbidity and functioning disability

The occurrence of an event (e.g., birth, death, education enrollment status, labor force participation) is decided by Monte Carlo simulation along with estimated transition probabilities. These transition probabilities depend on household or individual characteristics. The use of additional characteristics challenges the use of raw probabilities as the data becomes sparse across a high dimension of covariates. This challenge motivates the use of algorithms that can deal with the so-called “Curse of dimensionality.” In SMILE, the conditional inference tree (CTREE)

[3] We have not pursued a dynamic morbidity-labor force participation modeling in this paper. This would be an obvious extension to current work.
[4] Simulation Model of Individual Life-cycle Evaluation

algorithm has been a favored predictive classification method to address the challenge of high dimensionality and a more detailed description of its use in SMILE has been documented elsewhere (see Hansen et al. 2016). The CTREE algorithm is also used as to model morbidity and functioning disability.

In building predictive classification models, the set of predictors is limited to available information that already resides in SMILE since it would not be possible to implement the estimated transitions in the model otherwise. Additionally, cross-validation is used to select the optimal set of covariates for the CTREE.

A predictive model for the morbidity index
The morbidity transition probabilities are estimated using Danish administrative register data from 2013-2014. This dataset comprises approximately 4.5 million observations. The model consists of a three-step procedure. First, transition probabilities between morbidity states are estimated using the CTREE algorithm. Second, a classification model is estimated using the CTREE algorithm to get the probabilities of whether a person moves up or down in the index in the following period. Third, outcome probabilities are rescaled. For example, if a person is decided to move up in the index, all original outcome probabilities above the index value are rescaled proportionally to sum to 1.

Cross-validation decides the optimal predictive model among CTREEs with different combinations of predictors, given the constraint that these predictors must reside in SMILE. These predictors comprise the lagged morbidity index, age, gender, education level, labor market status, and spouse morbidity, but the optimal model only comprises the lagged morbidity index, age, and gender.

A predictive model for the functioning disability index
The CTREE algorithm is applied to a combination of SHARE and administrative data to estimate transition probabilities for limitations in ADL. The use of SHARE data put some limitations on the sample size and the age groups that are meaningful to include relative to the morbidity index, which is based solely on administrative data. SHARE targets people of age 50 or older that reside in one of the participant countries. The predictive model for the functioning disability projection simulations is based on data from the Danish subsample from waves 2, 4, and 5 in the SHARE-survey. The final sample only includes persons from SHARE that are identifiable in administrative data and respond to the question on limitations in ALDs. This selection results in a final sample of 6.281 observations. After testing different combinations of predictors, the optimal model is simply a CTREE where the functioning disability index depends solely on the morbidity index.

7. Modeling three morbidity scenarios

This section describes the modeling of morbidity expansion, dynamic equilibrium, and morbidity compression in SMILE. Common for all scenarios, mortality is estimated by augmenting the standard mortality estimation with the morbidity index, which is estimated using the CTREE algorithm. This estimation ensures a link between morbidity and mortality. The modeling does not necessarily follow the theories as outlined in Gruenberg (2005), Manton (1982), or in Fries (and colleagues) (1980; 2011). Instead, the modeling follows the stylized ways the literature presents the scenarios and ways that enable the modeling of the theories in SMILE.

Morbidity expansion

In the morbidity expansion scenario, transitions between morbidity states are constant over time. This feature ensures that the morbidity distribution at a given age and gender combination stays approximately[5] constant over time. Over time the mortality rate is scaled down proportionally across morbidity states by the expected decline in the age and gender-specific mortality from the national population projection. That is, the survival rate at any morbidity state for a given gender and age combination improves over time. The improved survival rate is arguably in line with a stylized morbidity expansion which predicts better survival chances of (chronic) disease without improvement in morbidity. This modeling results in a scenario where the mortality rate declines faster than improvements in the morbidity index leading to a morbidity expansion. The functioning disability index is modeled by a CTREE and depends solely on the morbidity index and thus follows the projected trajectory of the morbidity index.

Dynamic equilibrium

In dynamic equilibrium, the morbidity distribution is assumed to be unchanged at a given age and mortality declines by the expected decline in the mortality rate from the official national population projection. This part resembles the morbidity expansion scenario. However, the functioning disability index is modeled differently, to resemble that the disability impairment at a given morbidity state is less impairing on functioning. This modeling is performed by scaling down the probability of transitioning from a given morbidity state into a worse functioning disability state. This scaling is carried out in an iterative procedure. First, the probability of ending in the worst off group is scaled down by the expected decline in the mortality rate. The difference between the original and the scaled probability is then distributed proportionally across the remaining outcomes. Second, the updated probability of ending in the middle category is scaled down by the expected mortality rate decline. The difference between the updated probability and the downscaled probability is then assigned to the best of category. This procedure is used to move some from the worst to both the middle and the best functioning category, rather than just letting more persons move from the worst and the middle category to the best functioning category.

All things equal, a larger share of the population will be characterized by more disease for a given age group, but individuals' functioning will be less affected for a given disease which Manton (1982) theorized would be a plausible scenario. Thus morbidity for a given age group expands but is less lethal and less disabling. Only the former effect is modeled in the morbidity expansion scenario, whereas the dynamic equilibrium model implements both effects.

Morbidity compression

In a stylized morbidity compression scenario, the onset of chronic disease and death will concentrate in high ages implying that persons live a larger proportion of their lives in the absence of disease (Crimmins and Beltran-Sanchez, 2010). However, Fries (1980) does not provide any explicit trajectory into this scenario from the present state of morbidity in the population, and later he clarifies along with colleagues that morbidity compression is not inevitable (Fries et al. 2011). Thus some assumptions are needed to make a reasonable simulation of morbidity compression. First, the mortality rate is not scaled down for a given age, gender, and morbidity state by the expected decline in the mortality rate, such as in the morbidity expansion scenario. Instead,

[5] Noise from Monte Carlo simulation is also likely to add some noise to the results.

people's morbidity state improves by scaling morbidity transitions probabilities such that individuals at a given age have less risk of experiencing a worsening of their morbidity state and a higher chance of improving their morbidity state. Since mortality is (positively) correlated with morbidity, mortality declines. The scaling of morbidity transitions in favor of better morbidity states prolong the time spend in states with low morbidity and hence postpones the time of entering high morbidity states associated with high mortality.

Morbidity transition probabilities are scaled such that the age-specific number of individuals in the projection approximately matches the official national population projection. In specific, morbidity transitions are scaled by the expected gender and age-specific decline in the mortality rate. This scaling links the gender and age-specific morbidity improvement to the expected decline in the mortality rate. To some extent, this lends from the dynamic equilibrium theory that states, that mortality and morbidity will follow a similar trajectory, albeit with some deviations from the equilibrium at times (Manton 1982). This trajectory seems like a reasonable baseline since there is not formulated any explicit trajectory from the current state to morbidity compression.

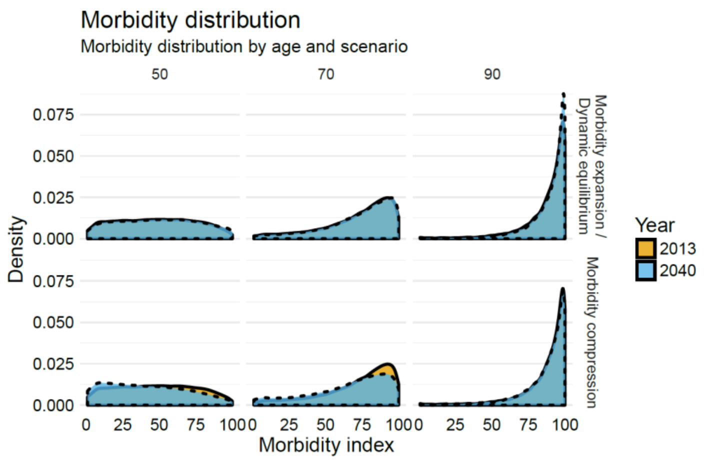


Figure 1, Source: Own calculation on SMILE

Notes: Morbidity transitions scaling is calibrated to target the official national population projection.

The scaling of morbidity transitions by the expected decline in the mortality rate leads to a somewhat optimistic scenario: at old age (e.g., age 90) up to 20% more individuals survive relative to the official national population projection. This improvement in survival occurs despite that mortality has not been scaled down as in the morbidity expansion scenario. To approximate results from the national population projection better, morbidity transitions are calibrated by reducing original scaling (see appendix for an example). An acceptable scaling is determined by visually inspecting the relative difference in numbers alive in the morbidity expansion and morbidity compression scenario. This calibration yields a baseline mortality compression scenario, which, to some extent, is connected to the expected mortality decline in the population projection. Figure 1 illustrates the effect on the projected morbidity distribution for the three scenarios against the distribution in the base year (2013). The distribution is approximately similar in the *morbidity expansion/dynamic equilibrium* scenario over time for a given age group but skews more towards improved morbidity in the *morbidity compression scenario* for ages 50 and 70.

Modeling three morbidity scenarios

The three scenarios are modeled using three steps.

1. The first step determines the morbidity state.
    a. A classification model is estimated using the CTREE-algorithm. Monte Carlo simulation determines whether a person moves up or down in the index using the estimated probabilities from the classification model.
    b. If a person moves up in the index, transition probabilities for indices above the current level are rescaled proportionally to sum to 1.
    c. Monte Carlo simulation then determines which level the person ends up in using only the levels above the current one and their associated rescaled transition probabilities from step 1.b.
2. In the second step, Monte Carlo simulation determines the functioning disability index, which is estimated by a CTREE where functioning disability depends solely on the morbidity index.
3. In the third step, Monte Carlo simulation determines whether a person dies using the estimated mortality. Mortality is estimated using a CTREE that uses the original predictors in SMILE but is augmented by the morbidity index. This augmentation ensures an association between higher morbidity states and lower survival rates.

In the morbidity expansion scenario, mortality (step 3) is scaled down over time by the expected gender and age-specific mortality decline from the official national population projection. This scaling is done proportionally across morbidity index values, such that survival chances improve by the same proportion across the morbidity index for a given gender and age combination.

The dynamic equilibrium follows the same modeling of mortality as in the morbidity expansion scenario. Furthermore, the transition probabilities of ending in worse functioning disability indices (step 2) are scaled down in favor of scaling up the probability of ending up in better functioning disability indices. Thus morbidity and mortality follow the same patterns as in the morbidity expansion scenario, but the dynamic equilibrium scenario is augmented by reducing the impact on functioning in a given morbidity state.

In the morbidity compression scenario, mortality *is not* scaled down as in the morbidity expansion and dynamic equilibrium scenarios. Instead, the classification model in step 1.b is modified by scaling down the probability of transitioning into a worse morbidity state over time and vice versa for the probability of transitioning into an improved morbidity state. This modification delays people in moving up in high morbidity states where mortality risks increase and by implication improve life expectancy.

8. Results

The development in both the mean of the morbidity index and functioning disability prevalence weighted across all seniors aged 50-100 is stagnation or worsening of both morbidity and functioning disability. That is the averaged composite effect of the change in the age composition and the age-specific development in morbidity or functioning disability. Morbidity worsens in the morbidity expansion/dynamic equilibrium but is stagnant in the morbidity compression scenario. Functioning disability worsens in the morbidity expansion scenario but is stagnant in the morbidity compression/dynamic equilibrium scenario. Below, results are examined in more detail.

Development in mean of the morbidity index weighted across all seniors (aged 50-100)
In the projections towards 2040, the mean of the morbidity index weighted across of all seniors (aged 50-100) increases in all three scenarios as illustrated in Figure 2. This increase is rather small in the *morbidity compression* scenario but more significant in the *morbidity expansion/dynamic equilibrium* scenario where it increases by two index points.

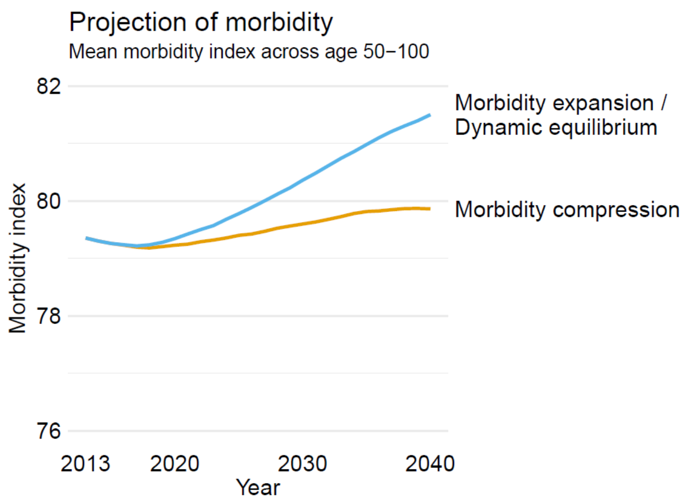
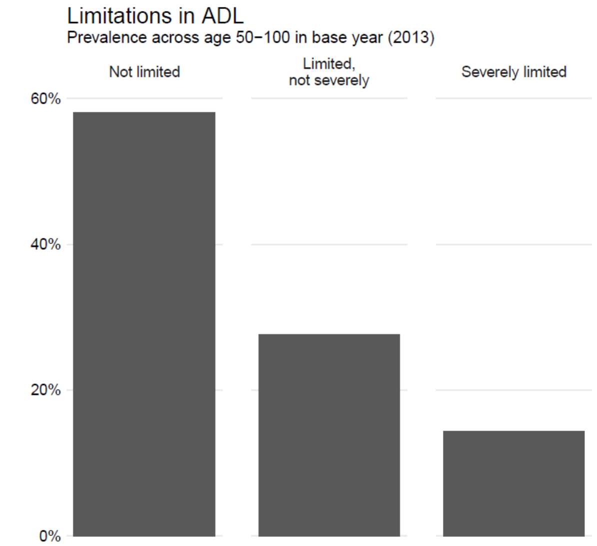


Figure 2, Source: Own calculation on SMILE

Development in functioning disability for seniors (aged 50-100)
Figure 3 shows the prevalence of limitations in ADLs across seniors aged 50-100. In the base year 2013, 58% are "not limited," while 28% are "limited, but not severely," and 14% are "severely limited." Figure 4 shows changes in each scenario in 2040 relative to the base year. In the *morbidity expansion* scenario, the prevalence of those "not limited" declines by 4.7% points. While the prevalence of "limited, but not severely" increases by 1.4% points, the share of "severely limited" increases by 3.3% points. In the dynamic equilibrium scenario, the prevalence of "not limited" also declines but only by 1.1% points. The prevalence of "limited, but not severely" declines by 0.6% points, while the share of "severely limited" increases by 1.7% points. In the *morbidity compression* scenario, there is no change in the prevalence of seniors that are "not limited," but there is a small substitution between "limited, but not severely" and "not limited." The former declines while the latter increases by 0.4% points. The overall effect is a small worsening in functioning disability.



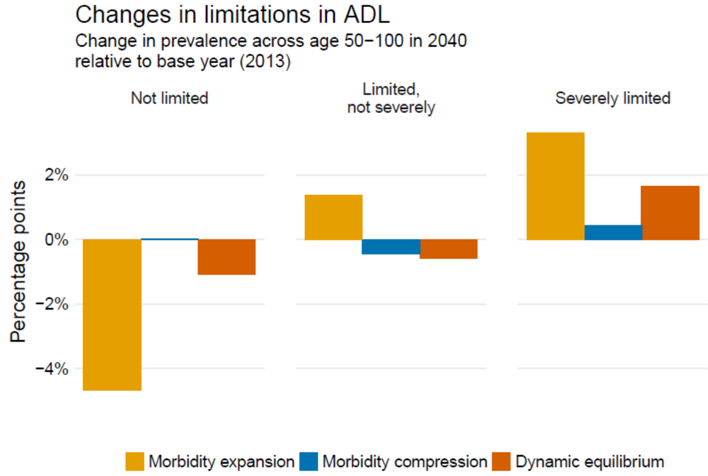


Figure 3, Source: Own calculation on SMILE

Figure 4, Source: Own calculation on SMILE

Development in the age-specific mean of the morbidity index

Figure 5 shows the development in the mean of the morbidity index over time in the *morbidity compression* and *morbidity expansion/dynamic equilibrium* scenario. The mean of the morbidity index either improves/decreases (*morbidity compression*) or worsens/increases slightly (*morbidity expansion/dynamic equilibrium*). The latter is likely caused by modeling noise from Monte Carlo simulation whereas the former is a consequence of the scaling the morbidity transitions. Since the age-specific morbidity improves or only worsens slightly in Figure 5, the change in the age composition of the population seems to outweigh age-specific development in morbidity in Figure 2.

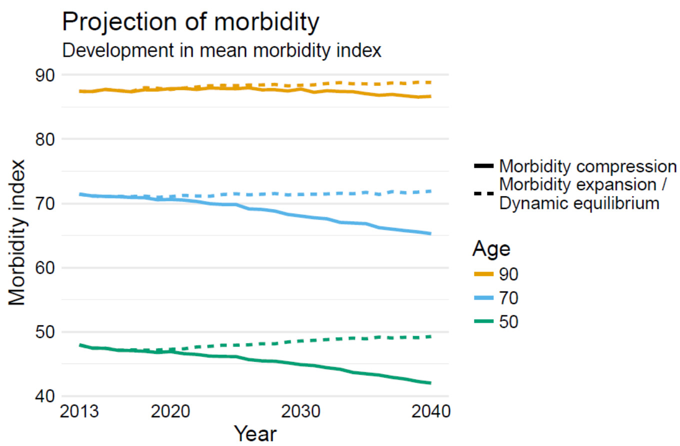


Figure 5, Source: Own calculations on SMILE

Development in the age-specific prevalence of functioning disability

Figure 6 shows the age-specific differences in the prevalence of limitations in ADLs relative to the base year for ages 50, 70, and 90. In the *morbidity expansion scenario,* the prevalence of seniors “not limited” declines in all three age groups, but mostly so for 90 year-olds. For all age groups, this results primarily in an increase in the prevalence of “severely limited.*”* The results in Figure 4 are thus driven both by the change in the age composition of the population and the age-specific worsening of functioning disability. The *morbidity expansion* and *dynamic equilibrium* scenarios resemble each other qualitatively with respect to age-specific functioning disability. The prevalence of “not limited” increases for age 50 and 70 but is relatively stable for 90-year olds. The prevalence of “limited, but not severely” and “severely limited*”* decline in both scenarios for age 50 and 70 but is broadly unaltered for the 90-year olds. The decrease in the prevalence of “severely limited” is more significant in the *morbidity* *compression* scenario. This decline is likely to explain why demographic effects are canceled out by age-specific effects in the *morbidity compression* scenario, but not entirely in the *dynamic equilibrium* scenario as shown in the overall results in Figure 4.

9. Discussion

Systematic reviews (e.g., Chatterji et al. 2015; Parker and Thorslund, 2007) find that evaluations of morbidity compression typically reflect the morbidity metric. Both reviews by Parker and Thorslund (2007) and Chatterji et al. (2015) finds no consistent support for any of the three predictions on morbidity trends but notes that some patterns seem to emerge from the literature. Studies examining morbidity using impairment-related measures more often find evidence for morbidity compression, whereas studies using (self-reported) chronic disease more frequently find evidence for morbidity expansion. Moreover, studies examining the morbidity severity do not find predominant evidence for any of the predictions, including dynamic equilibrium (Chatterji et al., 2015). In this light, it is perhaps not surprising, that effects in the simulations are limited although they do have differences between each other and relative to the base year. Of course, the simulation results depend strongly on (implicit) assumptions in the microsimulation model. While transitions probabilities are data-driven, they are also exposed to some calibration to avoid scenarios that are too optimistic relative to the official national population projection. Nevertheless, improvement in morbidity and functioning disability do not seem likely to outweigh the change in the age composition of the population.

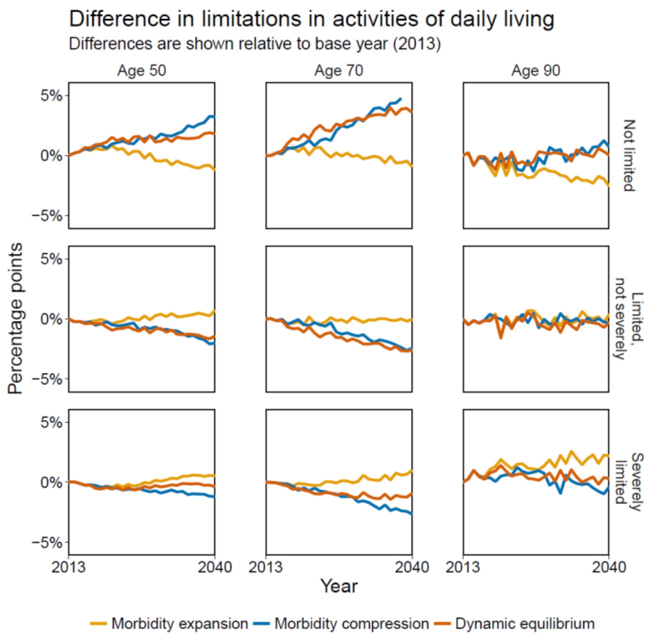


Figure 6, Source: Own calculations on SMILE

10. Conclusion

This paper has introduced a new methodology in assessing health/morbidity from human capital research (Bingley et al., 2014; Porteba et al., 2017) to morbidity compression research. This morbidity metric was used to project future morbidity scenarios in the elderly population. Additionally, this was used as a predictor to assess the prevalence of functioning disability in different projection scenarios. The theories of morbidity expansion, morbidity compression, and dynamic equilibrium were used to model different perspectives on future scenarios of morbidity and functioning disability. In all three scenarios, morbidity state transitions or mortality were scaled using the mortality rate decline in the official national population projection. Where needed, the scaling by the expected mortality rate decline was further calibrated to ensure minimal divergence between age-specific projection population counts in the official national projection and the morbidity projection scenarios.

In the *morbidity expansion* and *dynamic equilibrium* scenario, the mean of the morbidity index weighted across seniors aged 50-100 increases towards 2040, whereas it is stable in the *morbidity compression* scenario. Further, the prevalence of "severely limited" and "limited, but not severely" in ADLs increases slightly in the *morbidity expansion* scenario across the seniors aged 50-100. In both the *morbidity compression* and *dynamic equilibrium* scenario, there is a small substitution between the prevalence of "limited, but not severely" and "severely limited" in favor of the latter. In the *dynamic equilibrium*, there is both a small substitution from "not limited" and "limited, but not severely" to "severely limited." In the *morbidity expansion* scenario, the change in the age composition (demographics effects) mostly drives results. In the *morbidity compression* scenario, these demographic effects are largely canceled out by the age-specific morbidity improvement, whereas demographic effects dominate age-specific improvements in the dynamic equilibrium scenario. In sum, even if there are age-specific improvements in morbidity, it is likely that demographics will cancel this out because the composition of seniors will be characterized by older individuals relative to 2013. Thus, the overall morbidity and functioning disability amongst seniors are likely to worsen or appear similar to that of 2013.

11. Appendix: Calibration

Figure 7 shows the relative difference between the population in a projection aligned to the official nation population projection and the morbidity compression scenario where morbidity transition probabilities are scaled by the expected decline in the mortality rate from the official national population projection. While this difference is relatively small for ages 50 and 55, it increases in age and time. The difference is most significant for ages 85, 90, 95, and 100, where the difference ranges between 12% and 18% towards 2040. For ages 95 and 100, there is a large variability because samples get smaller for higher age groups. Nevertheless, the survival rate seems too optimistic in the scenario.

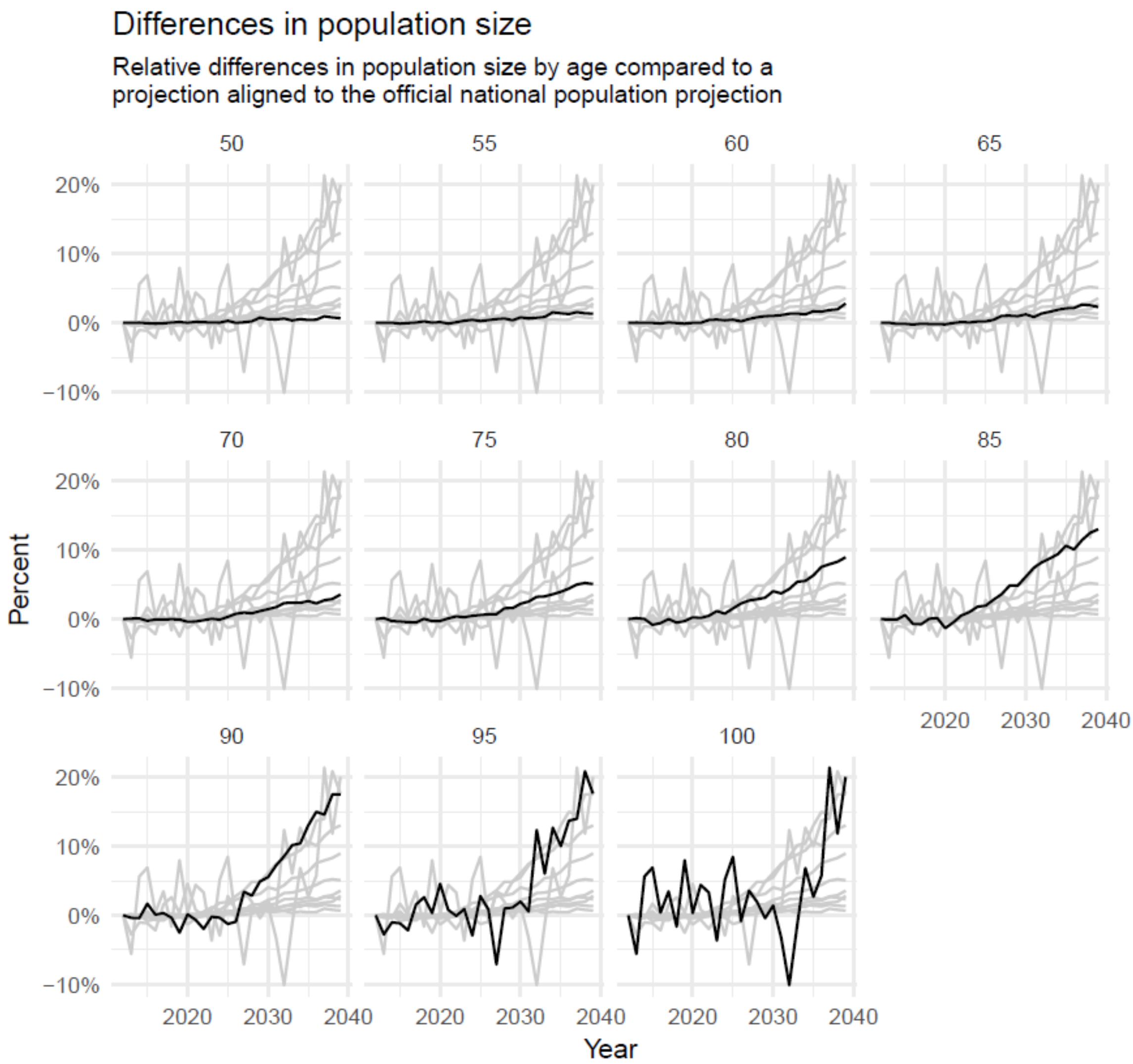


Figure 7, Source: Own calculations on SMILE

Figure 8 shows the relative difference between the populations in a projection aligned to the official nation population projection and the morbidity compression scenario with additional calibration. In this figure, the morbidity state transition probabilities are scaled by the expected decline in the mortality rate, which, in turn, are calibrated further to get the results below. In this case, which is the baseline for the morbidity compression scenario, the expected decline in the mortality rate is scaled down by 75 pct. Differences are relatively small except for high age groups. However, age group 95 and 100 also display high variability indicating that uncertainty associated with small samples drives results.

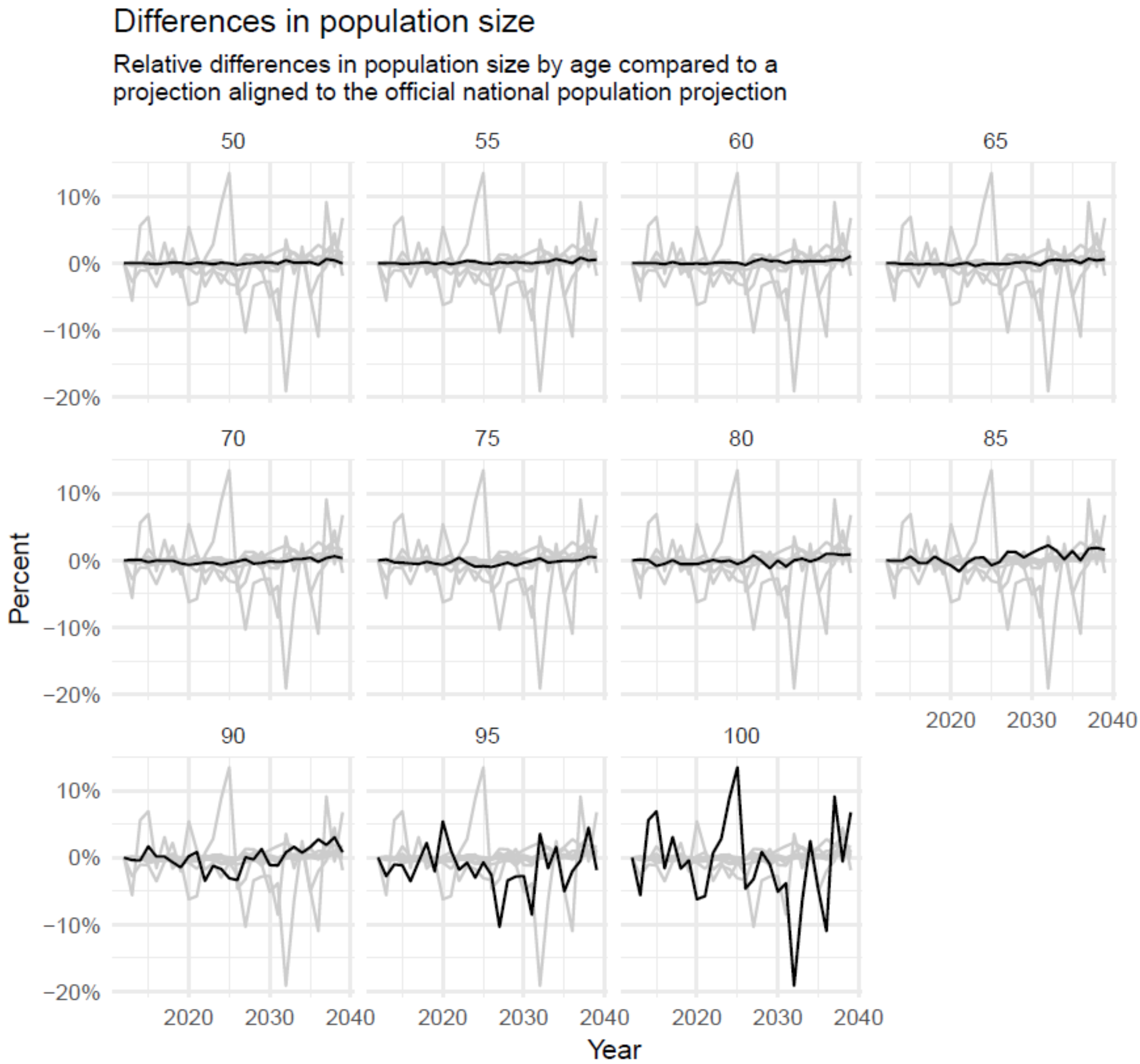


Figure 8, Source: Own calculations on SMILE

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