Individual health trajectories: population-based analysis of the effects of incidence and recovery

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Abstract

Lack of population-based analyses representative at a national level impedes better addressing health demands in the US elderly population. To understand age patterns of incidence and remission/recovery rates of aging-related diseases and their time trends, we analyzed individual histories of medical service use reconstructed from Medicare-linked datasets: the National Long Term Care Survey (NLTCS-M, 34,077 individuals followed-up for 5 years) and the Surveillance, Epidemiology and End Results (SEER-M, 2,154,598 individuals). Age, disability, and comorbidity patterns of incidence rates and time-after-diagnosis patterns of long-term remission/recovery rates were evaluated for cardio- and cerebrovascular diseases, most prevalent cancers, Parkinson's and Alzheimer's diseases, diabetes, and asthma. Decline in age patterns with age was detected for majority of diseases. Recovered individuals had higher survival and time trend in recovery rates were positive for all diseases except cancers. Estimates were validated using two Medicare datasets. Sensitivity analysis proved stability of evaluated rates.

INTRODUCTION

Determining the national trends in health and vital status in the population with growing proportions of elderly individuals is a major public health concern and important issue for policymakers and governmental institutions. To better address the health demands in the elderly and to reduce economic burdens on society, it is important to understand the key factors driving the onset and progression of aging-related chronic diseases. An identification of diseases age patterns with sufficient precision requires large population-based databases that are costly to collect. This is why studies on age patterns of diseases in the U.S. in elderly population and investigations of factors affecting them are rare. Therefore, this analysis is motivated by the lack of such comprehensive and representative analyses at a national level. Its results on estimates

of disease incidence and recovery rates for advanced ages are very valuable both in theoretical aspect of understanding the interaction of disease incidence and senescence, and for practical implementations for analyzing U.S. population health trends and forecasting future Medicare expenditures.

DATA and METHODS

Two Medicare-linked datasets (the NLTCS-M and SEER-M) used in the analysis contain information from the Medicare files of service use beginning from 1991. All individuals in the SEER-M and NLTCS-M are longitudinally tracked for Medicare Part A and Part B service use. Records on two of the six NLTCS waves, namely cohorts of 1994 and 1999, were chosen for detailed analysis primarily because the high quality of the Medicare follow-up data which are available only since 1991 and the complete 5-year follow-up after the NLTCS interview after 1991 is accessible only for these two waves. The NLTCS uses a sample of individuals drawn from the national Medicare enrollment files. In total, 34,077 individuals were followed-up for 5 years. So-called “screener weights” released with the NLTCS were used to produce the national population estimates. The collection of SEER data began in 1973 and currently covers about 26% of the U.S population. The SEER-M dataset includes Medicare records for individuals with diagnosed breast (n=353,285), colon (n=222,659), lung (n=342,961), and prostate (n=448,410) cancers, and skin melanoma (n=101,123), as well as Medicare records of 5% control. In total, Medicare records for 2,154,598 individuals are available in SEER-M.

Definitions of dates of onset and dates of recovery/remission. The ages at onset of all diseases

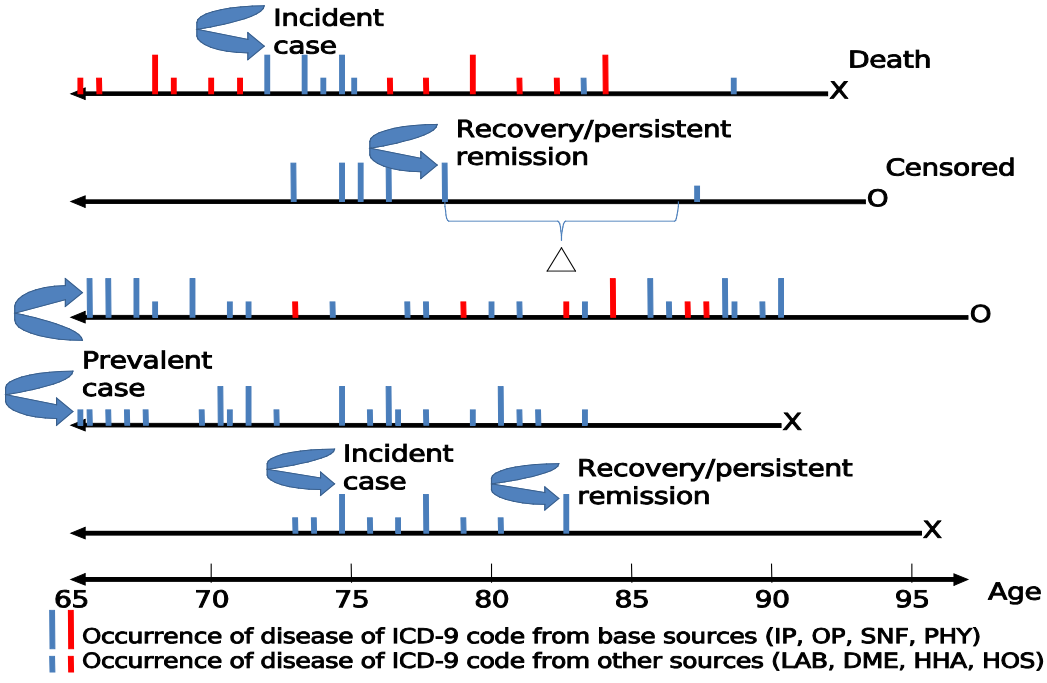

Figure 1. Individual health trajectories

and their recovery were reconstructed from the Medicare service use data using the following scheme. First, the individual medical histories of the applicable disease were reconstructed from Medicare files combining all records with their respective ICD-9 codes (Fig 1) for the considered diseases: acute coronary heart disease (ACHD) (410.xx, 411.xx, 413.xx), myocardial infarction (410.xx), angina pectoris (413.xx), stroke (431.xx, 433.x1, 434.x1, 436.xx), heart failure (428.xx), breast cancer (174.xx), prostate cancer (185.xx), skin melanoma (172.xx), lung cancer (162.xx), colon cancer (153.xx), diabetes mellitus (250.xx), chronic obstructive pulmonary disease (COPD) (490.xx, 491.xx, 492.xx, 493.xx, 494.xx, 495.xx, 496.xx), asthma (493.xx), emphysema (492.xx), chronic renal diseases with renal failure (403.xx, 404.xx, 585.xx, 250.4x, 249.4x), ulcer (531.xx, 532.xx, 533.xx, 534.xx), arthritis (714.0x, 714.1x, 714.2x, V82.1x), goiter (240.xx, 241.xx, 242.0x, 242.1x, 242.2x, 242.3x), Parkinson's disease (332.xx), and Alzheimer's disease (331.0). Then a special procedure was applied for individuals with the history of the considered disease to separate incident and prevalent cases, and to identify the cases of disease onsets and disease recovery/remission. This procedure was based on two conditions applied to each medical history. The first condition allowed for identification of the first appearence of the disease code, and the second was required for confirmation of disease presence. The individual Medicare history contains all records with respective disease ICD-9 code, however only records with primary ICD-9 code and only from the so-called base Medicare sources (inpatient care, outpatient care, physician services, and skilled nursing facilities) were used for the disease onset identification. This algorithm was used to study recovery after stroke (Yashin et al., 2010), medical cost trajectories before and after age-related disease onsets (Akushevich et al., 2011a), wide spectrum of geriatric diseases incidence using two Medicare based datasets (Akushevich et al., 2012), and the role of behavior factors in cancer risk (Akushevich et al., 2011b).

RESULTS

For the majority of considered diseases the obtained estimates were stable and in agreement with other studies. Figure 2 provides an example

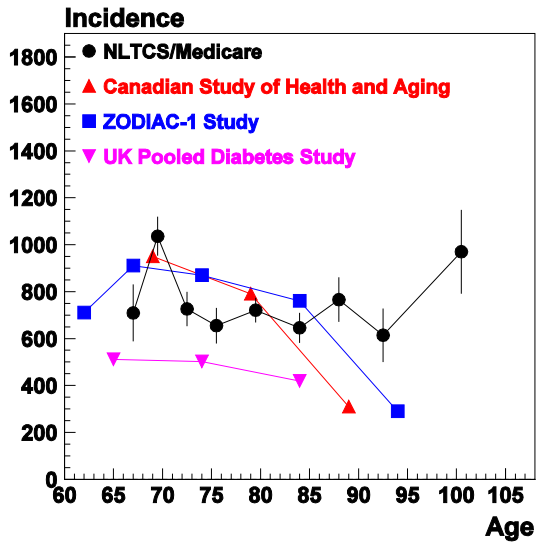

Figure 2. Age specific incidence rates for diabetes mellitus.

for age-pattern of diabetes calculated using the NLTCS-M and several other epidemiologic studies, such as Canadian Study of Health and Aging(Rockwood et al., 2000), Zwolle Outpatient Diabetes project Integrating Available Care (ZODIAC-1, the Netherlands, (Ubink-Veltmaat et al., 2003)), and UK Pooled Diabetes Study (Gatling et al., 2001). The age-patterns of acute and chronic disease incidence were evaluated using NLTCS-M and validated using the SEER-M. The results are presented in Figure 3 (Akushevich et al., 2012).

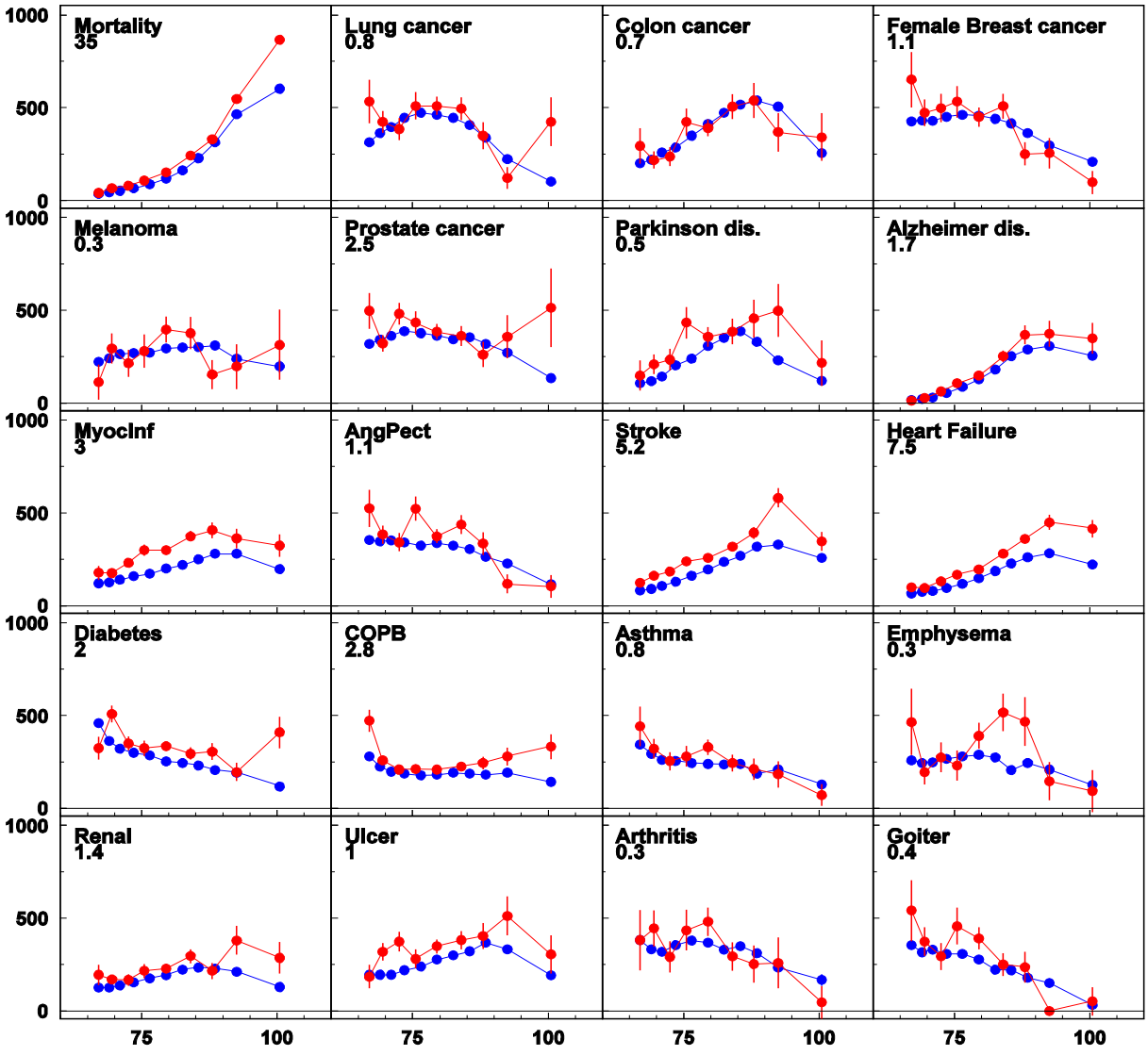

Figure 3. Age-specific rates of total mortality and disease incidence calculated using NLTCS-Medicare (red dots) and SEER-Medicare (blue dots). Values on plots are rescaled factors. Rates for different diseases are rescaled to use the same scale on all plots to compare rates for different diseases: the original rate can be calculated by dividing the values obtained from plot to the rescaled factor.

Age-adjusted sex- and cohort-specific rates of disease incidence were calculated using the NLTCS-M. Their comparison allows for estimations of time trends and male-female ratio (Figure 4).

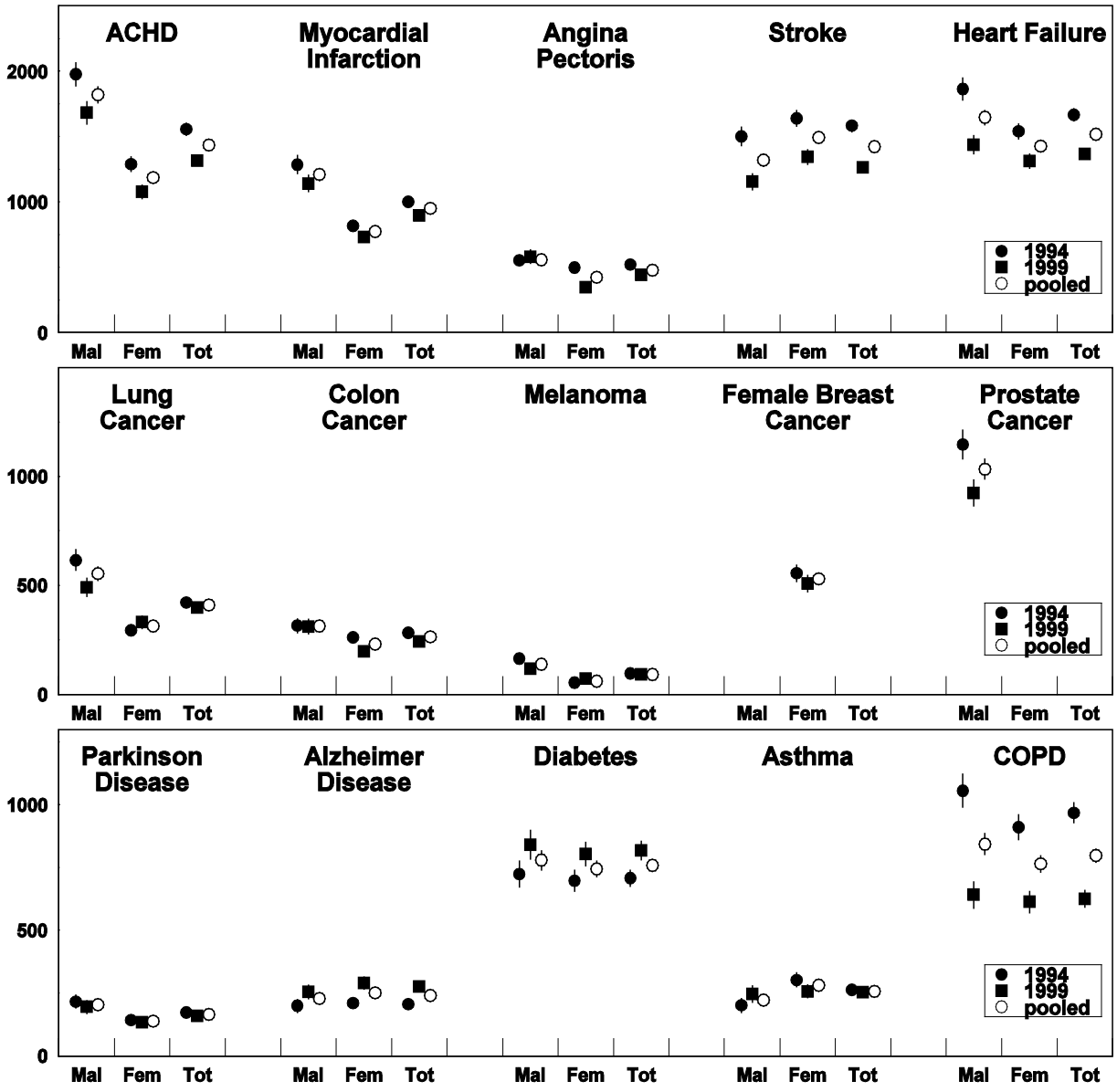

Figure 4. Age-adjusted incidence rates per 100,000 of circulatory diseases with standard errors.

Disability and comorbidity patterns were evaluated using the NLTCS-M data base (Table 1). For this calculation individuals were stratified by disability index (with outcomes nondisabled, IADL only, 1-2 ADLs, 3-4 ADLs, 5-6 ADLs, Institutionalized) measured at the date of interview, i.e., at the beginning of the follow-up, and by the Charlson comorbidity index according to the specifications described in (Charlson et al., 1987; Quan et al., 2005) also measured at the date of interview using Medicare records during a year prior to the date of interview.

Table 1. Disability and comorbidity patterns of the incidence rates (per 100,000) of geriatric diseases. Disability groups are nondisabled, IADL only, 1-2 ADLs, 3-4 ADLs, 5-6 ADLs, and institutional), and comorbidity group are in the units of the Charlson index (0, 1, 2, and 3 and more).

	Disability						Comorbidity			
	Non	IADL	1-2	3-4	5-6	Inst.	0	1	2	3+
ACHD	1442 (37)	1528 (183)	1596 (177)	1524 (244)	1997 (365)	947 (246)	1319 (43)	1384 (71)	1790 (126)	1930 (128)
Myocardial Infarction	917 (28)	1197 (151)	1188 (150)	1179 (165)	1304 (219)	1149 (245)	741 (32)	970 (54)	1309 (97)	1386 (91)
Angina Pectoris	475 (21)	485 (102)	592 (108)	793 (198)	643 (259)	224 (83)	422 (24)	492 (43)	500 (58)	740 (76)
Stroke	1294 (33)	2053 (220)	1885 (166)	3579 (468)	3621 (532)	2312 (339)	1182 (39)	1682 (78)	1557 (104)	2000 (104)
Heart Failure	1395 (35)	1964 (212)	2228 (209)	2934 (331)	3168 (440)	2454 (343)	1289 (41)	1798 (81)	1760 (98)	1907 (108)
Lung Cancer	413 (19)	395 (86)	594 (98)	417 (114)	223 (103)	313 (99)	306 (21)	578 (49)	451 (62)	518 (49)
Colon Cancer	264 (15)	534 (98)	322 (73)	167 (58)	288 (106)	59 (25)	241 (18)	295 (33)	354 (50)	225 (29)
Melanoma	90 (8)	120 (58)	99 (43)	310 (103)	44 (29)	25 (18)	79 (10)	68 (14)	122 (24)	142 (25)
Breast Cancer	554 (29)	480 (146)	404 (86)	416 (133)	108 (73)	272 (75)	532 (35)	657 (66)	464 (70)	363 (67)
Prostate Cancer	1068 (49)	904 (270)	1128 (275)	74 (60)	206 (92)	506 (195)	1165 (63)	1085 (109)	839 (121)	686 (121)
Parkinson Disease	146 (11)	242 (66)	231 (52)	334 (101)	376 (117)	446 (108)	151 (14)	167 (25)	202 (30)	176 (26)
Alzheimer Disease	217 (13)	413 (94)	231 (47)	416 (110)	159 (50)	516 (88)	204 (16)	242 (26)	282 (34)	311 (33)
Diabetes	738 (26)	651 (139)	911 (140)	1214 (278)	1157 (343)	802 (172)	783 (32)	794 (60)	679 (70)	691 (75)
Asthma	242 (15)	211 (63)	599 (132)	413 (103)	426 (157)	145 (53)	175 (16)	370 (40)	352 (42)	382 (62)
COPD	761 (28)	711 (166)	1295 (188)	1337 (288)	1159 (274)	1590 (421)	858 (36)	758 (60)	724 (73)	691 (74)

These results suggested that the national age-specific incidence patterns can be adequately evaluated from the Medicare Service Use Files.

Individual trajectories allow us to deal with the effects related to short- and long-term remissions occurring since the onset of a disease. Analyzing individual trajectories, we revealed a subgroup of patients who had stopped using medical services after a certain period of time following the diagnosis. Who are these individuals? Whether they are the healthier or sicker subgroup of patients? If they are healthier, then they could be those who i) have entered into a stable condition/long-term remission of chronic disease (in some cases such remission could be long enough that a “recovery” terminology could be used); or ii) have undergone a successful rehabilitation from acute diseases (e.g., myocardial infarction and stroke) without obvious complications affecting their quality of life. If they are sicker group, then they could be the patients who i) do not longer believe in doctors' recommendations after medical treatment failed to improve their health condition and/or did not improve their quality of life (as substitution, they could rely on treatment with naturalists, chiropractors, etc.); or ii) were not able to pay the treatment expenses; or iii) have moved to the areas (e.g., rural) where they lacked available transportation to reach doctor’s office for visits. To test the hypothesis, we used the Cox proportional model with age at diagnosis and time after remission (equal zero before remission).

Table 2. Hazard Ratios per one year. All effects are statistically significant.

Disease	Sex	SEER-Medicare		NLTCS-Medicare	
		Time after remission	Age at diagnosis	Time after remission	Age at diagnosis
ACHD	male	0.768	1.090	0.712	1.095
ACHD	female	0.794	1.087	0.735	1.083
Stroke	male	0.814	1.064	0.779	1.069
Stroke	female	0.787	1.071	0.819	1.072
Ulcer	male	0.712	1.072	0.439	1.095
Ulcer	female	0.711	1.074	0.627	1.062
Breast cancer	female	0.727	1.083	0.658	1.091
Prostate cancer	male	0.880	1.102	0.801	1.085
Melanoma	male	0.650	1.078	NS	1.127
Melanoma	female	0.745	1.099	0.555	1.023
Lung Cancer	male	0.417	1.027	0.562	1.040
Lung Cancer	female	0.492	1.029	0.391	1.028
Colon Cancer	male	0.554	1.055	0.683	1.078
Colon Cancer	female	0.571	1.060	0.393	1.068
Asthma	male	0.887	1.083	NS	1.091
Asthma	female	0.900	1.095	NS	1.074

NS—non-significant

Results in Table 2 showed that the patients with large periods which lack of appearance of new and re-appearance of previously existing ICD-9 records are the healthier subcohort. The Kaplan-Meyer estimates of not-yet-recovery probabilities are presented in Figure 5. Comparison of curves for different time periods showed that the time trend is positive (remission increases) for the majority of acute and several chronic diseases, excluding cancers.

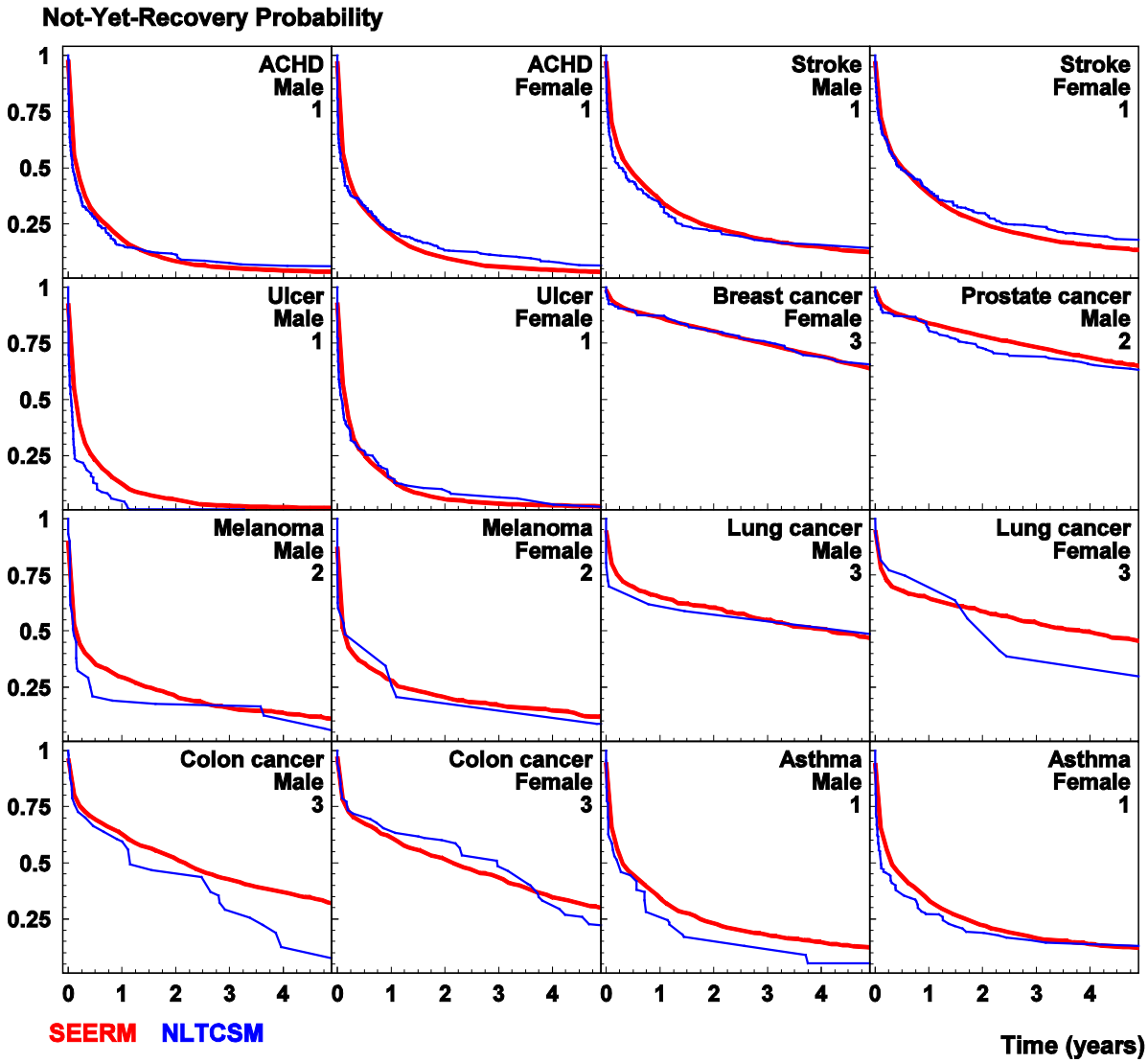

Figure 4. "Not-yet-recovery" probability for geriatric diseases vs. time after diagnosis in years calculated using SEER-Medicare (red thick lines) and NLTCS-Medicare (blue thin lines). Values on plots are "recovery" times, i.e., disease-specific time period without occurrence of respective ICD code in individual medical (Medicare) history.

Sensitivity analysis.

A disadvantage of large administrative databases is in the presence of factors producinsystematic over-/underestimation of the number of diagnosed diseases or of the age at onset. One reason for such uncertainties concerns the incorrect date of the disease onset. Other sources are the latent disenrollment and effects of study design. To evaluate the effect of these uncertainties, we performed the calculations with different definitions of disease onset, and used alternative censoring schemes to define individual observation periods. Table 3 presents the results of calculating age-adjusted rates from the NLTCS-M data using several alternative approaches. We can conclude that the calculated rates are relatively stable. Thus, columns V1-V3 represent calculations without age standardization using standard population of 1994 (V1) and without using NLTCS sample weights (V2). In the alternative censoring scheme (V3), the last day of observation is the latest day among i) part B coverage, ii) Medicare record in Part A or Part B, iii) response on interview in the next NLTCS wave, while in the basic calculation, the final date of observation is the earliest date among dates of disease onset or death, and the last date of cohort observation. Only minor changes in incidence rates obtained within V1-V3 strategies were detected. The results of calculations V4 and V5 reflect the effect of removing individuals from the cohort with different level of additional coverage by HMO (exactly, by different fractions of months covered by HMO denoted by δ). Since individuals covered by HMO supposed to be healthier than general elderly population, the obtained decline in the incidence rates under V4 and V5 strategies is expected. Other calculations represent less (V6-V10) or more conservative (V11) approaches to the definition of the date at onset. In each of the approaches one of the components of definition is replaced by alternative one.

The sensitivity study for time trend in recovery after stroke was performed by (Yashin et al., 2010). The effects i) several different operational definitions of recovery and incidence rates; ii) explicit representation of observed heterogeneity effects stratifying individuals on age, comorbidity, or disability; and iii) other approaches to censoring strategies, selection of individuals, and study design effects. The results of the analyses indicated that positive trends in the recovery rate from stroke took place in all cases independent of the definition of such rates.

Table 3. Age-adjusted incidence rates per 100,000 under alternative approaches to the definition of age at onset calculated for specific sex (S) and year (Y) of the cohort forming. Standard calculation (V0) of age-adjusted incidence rates (per 100,000) was performed according to the aforementioned rules, i.e., screener NLTCS population, using the NLTCS weights, the 4 basic Medicare sources, only the primary diagnosis, at least two records (or death) in $\Delta = 0.3 years$, with cut on frequency of HMO coverage $\delta = 0.05$, age standardization using standard population of 1994. Other calculations are: V1) no age standardization, i.e., age specific rates are averaged using population of respective year, V2) No NLTCS weights, V3) alternative censoring strategy, V4) $\delta = 0.5$, V5) $\delta = 1$, V6) all Medicare sources, V7) $\Delta = 0.5 years$, V8) no requirement for codes to be primary, V9) no requirement of the second record (Algorithm B), V10) no both requirement from V8 and V9, and V11) no death as a second event.

	S	*Y*	*V0*	*V1*	*V2*	*V3*	*V4*	*V5*	*V6*	*V7*	*V8*	*V9*	*V10*	*V11*
ACHD	*M*	*94*	1977	1954	2013	2027	1969	1739	1754	1814	2467	3553	5151	1576
	M	*99*	1681	1684	1737	1769	1743	1446	1470	1540	2099	2915	4270	1335
	F	*94*	1290	1274	1264	1266	1217	1113	1151	1225	1696	2560	3940	995
	F	*99*	1076	1077	1097	1102	1098	944	950	997	1432	2238	3291	842
Myocar-dial Infarction	*M*	*94*	1287	1258	1309	1317	1242	1115	1144	1151	1493	1737	2446	954
	M	*99*	1141	1141	1197	1215	1193	996	1013	1018	1227	1587	2080	885
	F	*94*	816	791	782	783	756	695	723	738	947	1221	1728	570
	F	*99*	729	731	764	767	746	648	662	662	868	1030	1403	544
Angina Pectoris	*F*	*94*	552	541	566	569	581	510	545	558	980	1812	3147	466
	F	*99*	579	581	560	570	579	475	480	526	855	1497	2493	453
	M	*94*	499	496	500	501	480	433	466	499	870	1470	2517	398
	M	*99*	349	349	351	353	369	306	309	343	646	1230	2024	295
Stroke	*M*	*94*	1501	1441	1458	1468	1404	1251	1353	1314	1582	2332	3046	1060
	M	*99*	1155	1156	1168	1185	1190	1003	1072	1047	1306	1983	2720	854
	F	*94*	1640	1595	1583	1587	1536	1430	1525	1519	1770	2568	3311	1239
	F	*99*	1344	1343	1333	1338	1307	1116	1196	1171	1447	2165	2922	987
Heart Failure	*M*	*94*	1864	1795	1869	1881	1784	1612	1706	1767	2713	3055	5345	1389
	M	*99*	1437	1438	1465	1486	1501	1312	1367	1445	2292	2659	4670	1215
	F	*94*	1540	1484	1511	1515	1476	1346	1458	1511	2348	3009	5084	1189
	F	*99*	1313	1313	1323	1329	1349	1185	1274	1301	2042	2500	4397	1084
Lung Cancer	*M*	*94*	616	613	618	623	593	529	572	541	629	657	839	454
	M	*99*	491	490	488	495	484	432	511	462	496	612	711	373
	F	*94*	293	295	280	281	269	248	278	258	288	368	455	220
	F	*99*	331	330	332	333	322	289	342	302	324	393	454	264
Colon Cancer	*M*	*94*	314	306	302	304	280	253	269	267	289	427	483	224
	M	*99*	311	311	321	326	322	296	308	300	356	440	526	270
	F	*94*	262	259	252	253	243	232	245	237	264	349	432	218
	F	*99*	196	195	194	195	192	177	200	187	200	282	361	170
Melanoma	*M*	*94*	163	159	161	162	149	131	131	137	142	225	277	110
	M	*99*	117	117	130	132	135	113	113	119	131	204	257	106
	F	*94*	53	51	49	49	45	42	44	46	57	139	166	36
	F	*99*	71	70	76	76	76	63	63	64	65	99	127	63
Breast Cancer	*F*	*94*	555	559	572	573	541	498	508	511	544	802	906	485
	F	*99*	508	509	512	514	496	432	454	442	453	580	674	424
Prostate Cancer	*M*	*94*	1146	1148	1116	1125	1098	984	996	1033	1102	1649	2044	944
	M	*99*	924	922	950	967	939	808	817	876	913	1305	1675	792
Parkinson Disease	*M*	*94*	217	208	221	223	213	190	199	205	272	289	465	183
	M	*99*	195	195	186	189	179	156	159	171	313	282	531	150
	F	*94*	143	139	140	140	135	121	133	128	222	216	405	116
	F	*99*	134	134	127	127	130	117	130	130	216	209	413	107
Alzheimer Disease	*M*	*94*	199	187	200	201	192	174	179	194	396	343	737	151
	M	*99*	255	257	245	247	242	219	246	262	462	540	992	183
	F	*94*	210	197	192	192	189	183	225	221	532	439	1048	157

	F	*99*	290	291	287	288	296	264	301	323	717	670	1457	239
Diabetes	*M*	*94*	724	721	718	723	725	681	715	772	1303	1787	3403	646
	M	*99*	841	841	801	816	884	784	878	936	1478	2130	4158	739
	F	*94*	697	696	702	704	707	650	678	728	1179	1665	3197	611
	F	*99*	803	804	797	801	799	713	818	827	1260	1835	3636	673
Asthma	*M*	*94*	201	200	202	204	198	174	198	211	395	744	1484	157
	M	*99*	247	248	263	267	260	228	260	255	478	723	1591	206
	F	*94*	303	307	309	310	301	287	329	316	550	934	1692	278
	F	*99*	258	257	228	229	239	213	274	232	525	842	1679	200

DISCUSSION and CONCLUSION

The disease incidences and recovery/remission rates were analyzed for aging-related conditions representing the major groups of chronic diseases in elderly: i) circulatory (ACHD, myocardial infarction, angina pectoris, heart failure, and stroke), ii) cancer (breast, prostate, lung, and colon cancers, and skin melanoma), iii) neurodegenerative (Parkinson's and Alzheimer's diseases), iv) endocrine and metabolic (diabetes mellitus and goiter), v) pulmonary (COPD, emphysema, and asthma), and vi) several other (chronic renal diseases, ulcer, and arthritis). The set of these diseases carries the major population burden for the US elderly population resulting in high medical expenditures. Both age-adjusted and age-specific (as well as disability-, and comorbidity-specific) rates were calculated using the NLTCS data linked to the Medicare service use files. The study design of the NLTCS allows for projecting the estimates for the whole US population, so the rates are valid at the national level. The strategy for identifying the dates of onset is based on analysis of complete trajectories of individual records associated with the selected diseases. The most appropriate scheme for the onset identification requires forthcoming occurrence of repeated claims containing chosen ICD codes as a prime diagnosis in basic Medicare sources. The possible sources of biases in this basic strategy were analyzed and their contributions to incidence rates were estimated.

The comparison of the age patterns with other studies, as well as their sex differences and time trends, demonstrated the similarities with patterns obtained in other population studies in the U.S. and other countries. The patterns of the majority of diseases could be well described by the base algorithm, the most important features of which include occurrence of the primary diagnosis in one of four Medicare sources (inpatient care, outpatient care, physician services, and skilled nursing facilities), and the confirmation of the diagnoses in another record. Patterns of several diseases require certain corrections to the base algorithm to be adequately described. For example, only one record has to be required for ACHD. Another example is

Alzheimer's disease for which also only one record is sufficient and this record need not be primary.

The disability and comorbidity patterns of disease incidence were also evaluated. Disability was measured using self-reported information, while comorbidity was estimated using Medicare records during the year prior the date of interview and beginning of 5-year follow-up period. Because of using the sample weights, the results are valid at the national level. Occurrence of the shapes with a maximum and, especially, with monotonic decline contradicts the hypothesis that risk of geriatric diseases correlates with accumulation of adverse health events (genetic mutations, deterioration of vascular system, immunosenescence, etc.). Thus, comparing the age patterns obtained by using the basic strategy with those available in the literature showed a good agreement for the majority of diseases; however, for ACHD and Alzheimer's disease the adjustments have to be made. The performed analyses suggested that the national age-specific incidence patterns can be adequately evaluated from the Medicare service use files.

Remission/recovery rates for aging-related diseases and their time trends are detectable using Medicare data. We proved that patients for whom large periods lacking in ICD-9 records are the healthier subcohort. Time trend is positive (recovery increases) for majority of acute and several chronic diseases, excluding cancers. The detected sex difference in such trends may partly be caused by different attitudes toward the use of health care services in males and females.

Usefulness of the Medicare data is important because there are few data sources to study such incidence patterns at advanced ages in the national population. For example, heart disease and stroke account for more than 40% of all deaths among persons aged 65 to 74 years and almost 60% of those aged 85 years and older, however there are no nationally representative data available on incidence, severity, or recurrence of acute coronary or stroke events in either the inpatient or outpatient settings, with the performance measures which are not consistent across databases. Therefore, the linked NLTCS-Medicare data could be very useful in estimating incidence of aging-related diseases and associated medical costs, as well as comorbidities and disability in the U.S. elderly. In addition, an advantage of the Medicare data is the relation of these age specific incidence patterns to Medicare costs, and—via the NLTCS files—to disability incidence. Such a dataset is extremely important in projecting future Medicare costs. So, the results reported in this study are timely and important as they may inform current scientific and policy debates about the effects of biomedical research and

therapeutic innovations on disease incidence at increasingly advanced ages when the effective therapeutic interventions were introduced.

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