METHOD FOR MEASURING THE RATE OF IMPROVEMENT IN SURVIVAL TIMES OF CANCER PATIENTS

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Abstract

In clinical settings, technological advancements have facilitated health care improvements in data analytics, artificial intelligence, telemedicine, health information systems, etc. This has furthered our understanding of cancer biology and treatment mechanisms. In this study, we aim to understand whether Moore's law-like models may derive from historical cancer survival data, and how they can predict survival statistics for newly diagnosed cancer patients. Historically these predictions have previously been done with the diagnosis year as the independent variable and the survival as a dependent variable. In this study we use death year data as an independent variable and from that, we derive 5-, 10- and 20-year survival times. This will help us determine the best fitting curves for determining recent cancer survival times as well as future survival times. To do so, we use publicly available SEER data to obtain average cancer survival time data while avoiding recency bias.

Dedication

In memory of my late grandmother, Margaret Thobani Shaba, whose wisdom continues to guide me from afar, and my late in-laws (Varaidzo Loveletter & Abner Chaduka) who were tireless proponents for education.

First and foremost, I give all glory to God. Without Him, none of this would have been possible.

To my entire family and wonderful in-laws, whose love, support, and encouragement have been the foundation of my journey, this work is dedicated with profound gratitude and love.

To my parents (Norah & Titus Shaba), especially my father, whose unwavering belief in the power of education and desire to see his children reach the highest levels of achievement have been a driving force in my life. Both your sacrifices and support have been my constant motivation.

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And finally, and to my precious daughter Varaidzo Loveletter. Your arrival has filled my life with renewed purpose and joy. I hope this inspires you the way you inspire me every day.

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Introduction

Moore's law is an observation that has profoundly influenced the development and evolution of the semiconductor industry and modern technology (Schaller, 1997). The law, named after Intel co-founder Gordon E. Moore, refers to the observation that the number of transistors on a microchip doubles approximately every two years, while the cost of these components decreases at a similar rate (Moore, 1975). This phenomenon has had a revolutionary impact on the performance, efficiency, and cost of electronic devices, laying the foundation for the information age we live in today including healthcare technology (Keyes, 2006).

A particular problem yet to be fully understood in cancer research pertains to survival estimations for newly diagnosed cancer patients (Deepa & Gunavathi, 2022). Although survival estimations exist and are constantly updated, this data is frequently based on historical data (Brenner et al., 2004). This paper focuses on how exponential or other trajectory curves for advancements of technologies, as predicted by, for example, Moore's law, helps enable the development and implementation of predictive models for kidney and other cancer survival times. The outcomes of findings will be useful for clinicians, researchers, policy makers, and most importantly, patients.

Background

The origins of Moore's law can be traced back to a paper published in 1965 by Gordon E. Moore, who was working at Fairchild Semiconductor at the time (Brock, 2006). In his paper titled "Cramming more components onto integrated circuits," Moore observed that the number of transistors on a chip had been doubling every year since the invention of the integrated circuit in 1958, and he predicted that this trend would continue for at least ten more years (Schaller, 1997).

Over time, this prediction evolved into the more widely accepted version of doubling approximately every two years (Brock, 2006).

The driving forces behind Moore's law are multifaceted. One of the primary factors is the advancements in semiconductor manufacturing processes (Keyes, 2006). Engineers and scientists have consistently found ways to make transistors smaller and pack more of them onto a single chip (Schaller, 1997). This miniaturization has allowed for increased computing power and energy efficiency (Ning, 2019). Over time, leading companies in the field of research and development continue to invest heavily in cutting-edge technologies, which has facilitated the continuous refinement of fabrication techniques and the discovery of new materials (Brock, 2006).

Impact on Technology

Moore's law has had a transformative impact on modeling the technology landscape. It has been the driving force behind modeling the rapid growth in computational power and the reduction in the size and cost of electronic devices (Schaller, 1997). The continuous improvement in computing capabilities has fueled innovations in various fields, including telecommunications, medicine, entertainment, and artificial intelligence (Young, 2019). As transistors became smaller and more efficient, electronic devices such as computers, smartphones, and tablets became more powerful, compact, and affordable (Brock, 2006). This has led to an explosion in the availability and accessibility of technology, revolutionizing how people communicate, work, and entertain themselves (Kirilenko & Lo, 2013).

Moore's law and Health Care Technology

While Moore's law directly pertains to the exponential growth of transistors on microchips, it has indirectly contributed to the advancement of computational power and data

processing capabilities (Mulay, 2015). These advancements have facilitated complex simulations, data analysis, and AI applications, which are increasingly being used in cancer research and treatment planning (Westwood, 2002). The ability to process vast amounts of data quickly and efficiently has accelerated progress in oncology and furthered our understanding of cancer biology and treatment mechanisms (Schulmeister, 2016). Researchers and engineers are exploring alternative technologies, in order to continue the trend of increased computing power. However, the future trajectory of Moore's law in computing remains uncertain yet hopeful.

Moore's law and Survival Estimations

Survival estimation refers to the process of predicting the time until an event of interest occurs, often in the context of medical research or reliability analysis (Wang et al., 2019). It involves statistical methods to analyze data and predict the time until an event (like death or equipment failure) happens. Survival time should not be confused with mortality. Mortality is the probability that a person in the population will die of a specific cancer over a certain time period, usually a year. (Mariotto et al., 2014).

Keeping Moore's law in mind, it is generally accepted that healthcare technology improvements have enhanced survival estimations by enabling earlier and more precise diagnoses, personalized treatments, better monitoring, and improved overall patient care (Gallacher et al., 2021). These advancements collectively contribute to extending and improving the quality of life for individuals with various medical conditions (Marino & Lorenzoni, 2019). The focus of this study is to investigate to what degree some of these improvements lead to enhanced survival time estimations. To do so, we utilize publicly available cancer data. We hypothesize that survival time is increasing and that the rate of increase may be modeled as a new application of Moore's law for cancer survival times.

Problem Statement

This paper explores the growth, as predicted, for example, by Moore's law, of cancer survival time. It is agreed that survival estimates using cancer registry data are often dated measures of current-year survival, because of the time needed to observe survival and the lag between available data and the current year (National Cancer Institute, 2022a). Utilizing SEER data, some of the key research questions this paper plans to investigate are:

1. Using previous years' survival statistics data, can a Moore's law model be derived based on historical trends in specific cancer survival data?
2. Can the model above be used to predict a survival statistic for a patient that has recently been diagnosed with a given cancer?
3. How does the overall trend from #2 match a Moore's law model?
4. How consistent are Moore's law predictions with those of linear and logistic models?

2. Literature Review

Cancer survival estimation provides insights into disease progression, treatment efficacy, and overall patient outcomes (Mariotto et al., 2014). A challenge associated with estimating long-term survival lies in the fact that only cohorts diagnosed many years ago possess adequate follow-up data to directly calculate these measures. Consequently, direct estimates of long-term survival may lack relevance for newly diagnosed patients, particularly in cancers that have witnessed remarkable advancements in survival rates (National Cancer Institute, 2022a). Traditional methods of calculating survival rates rely on historical data and assumptions that may not accurately reflect the current pace of medical advancements. This literature review explores the potential application of Moore's law, which is a name for an exponential model of growth over time, to calculate more up-to-date cancer survival estimates based on the date of death.

Related Work

Survival Prediction in Other Domains

Many attempts have been made to produce more reliable survival estimates. For example, authors Brooks et al. (2000), utilize the Bayesian model to estimate the lifetime of the blue-winged teal as well as the Cormack-Jolly-Seber model to estimate European dippers. While the paper opens new avenues for research in the field, it also prompts important questions for future investigations, including the exploration of complex models within the Bayesian framework, the impact of environmental variables on animal survival, and the development of user-friendly tools for researchers. Although the paper doesn't directly compare Bayesian methods to traditional frequentist approaches in mark recovery and recapture studies, it presents a novel application of Bayesian statistics to this specific context.

Davis et al. (2007) attempt to predict when new types of water pipes, like PVC, might start to fail in the future. For older pipes, like cast iron or asbestos cement, one can use past data to make predictions because there is a lot of information about how they break. But for newer pipes like PVC, there is an insufficient amount of data to make accurate predictions. In summary, this paper introduces a new way to estimate when PVC pipes might fail. It uses a model that looks at things like cracks in the pipe and the pressure of the water inside. They also consider that these defects in the pipes can vary in size and use a special math tool to account for this variability. Using a Monte Carlo simulation, they estimate the chances of PVC pipes failing over time. This method helps to include all the uncertainties in the predictions, which helps researchers understand when and why new types of water pipes might break, even if we don't have a lot of data about them (Davis et al., 2007).

Alam & Suzuki (2009) try to solve a similar problem to our problem statement. Although the focus pertains to products in the manufacturing industry, it is still very relevant. The authors seek to understand how long products last and how reliable they are. Manufacturers want to know this information to make better products. They often use warranty data to figure this out because it's easy to get data from warranty claims when products break. For engineers and product designers, it's more important to know how long a product can be used before it breaks, like how many miles a car can be driven before it needs major repairs. The problem is that warranty data only tells us about the products that have failed, not the ones that are still working fine. In their paper, the authors demonstrate shows that they can estimate how long products last based on warranty data, even without information about products that haven't failed. This is important because it means they don't always need extra data about products that are still

working well to figure out how reliable a product is. This finding can help manufacturers make better products without the need for expensive additional studies (Alam & Suzuki, 2009).

Barreto-Souza & Bakouch (2013) introduce the exponential Poisson-Lindley (EPL) distribution as a novel means of understanding product lifetimes. The authors are particularly interested in this method to help researchers understand products that have decreasing failure rates over time. The authors demonstrate how, for this situation, their new method is more suitable than other methods for modeling the time it takes for something to fail. For example, it could be helpful for predicting when a device might stop working. In the future, they plan to use this method to study systems made up of many parts, where everything stops working when even one part fails. This may help researchers make better predictions about the overall lifespan of complex devices and systems (Barreto-Souza & Bakouch, 2013).

Authors Howell et al. (2019) present insight into the field of space technology by demonstrating that trends in the mean lifespan of satellites sometimes follow an exponential pattern thus being a Moore’s law. This observation challenges the conventional thinking about technological advancements in space travel progress. The paper identifies both Wright's law and Moore’s law regressions, indicating that the lifespan of satellites may double with an increase in accumulated launches, and that the doubling time for Moore’s law in the context of space travel is, historically, approximately 15 years. This revelation has significant implications for industry, science, and government policies related to space technology, as it underscores the need for adaptive strategies and increased investment in this rapidly evolving field (Howell, Kodali, Kreinovich, et al., 2019).

Questions for future research include delving into the specific factors driving the observed trends in satellite lifespan, understanding the practical implications of these trends for

space exploration and satellite deployment, and assessing the sustainability and environmental impact of increasing satellite launches as suggested by Wright's law. Furthermore, the conundrum generated by the application of Moore's law in the context of space travel, as explained by Howell, Kodali, Kreinovich, et al., (2019) requires further investigation to gain a deeper understanding of the dynamics involved. While the paper doesn't provide detailed insights into the practical implications of the identified trends, it introduces a novel perspective on technological development in space travel and highlights the importance of monitoring exponential trends in various domains (Howell, Kodali, Kreinovich, et al., 2019).

The same year, Howell and his colleagues (2019a) empirically examined and mathematically modeled technological progress in the domain of space travel, specifically focusing on the lifespan of satellites. Their findings identify both Wright's law and Moore's law regressions as potential models for describing the trends in satellite lifespan. The authors use the models to predict a future deviation from the observed Moore's law trend, suggesting that satellite technology may not continue to fit an exponential function of satellite year of death. The study primarily focuses on theoretical aspects and mathematical trends, leaving room for future research to bridge the gap between theory and practical applications in the context of space technology. This has important implications for the space industry, influencing research, policy, and investment decisions (Howell, Kodali, Segall, et al., 2019a).

In 2022, Batthula (2022) conducted a trend analysis on average satellite lifetimes. Instead of humans or animals, the focus of the study is on product lifetime, with the product being space satellites. Using existing satellite launch data, Batthula identifies the half-life of space satellites and how it changes depending on launch year cohort. The author utilizes satellite half-lives to

address recency bias of satellites still in orbit. This data is utilized to project future lifetimes of satellites based on the year of launch (Batthula, 2022).

Estimations may be utilized in various ways. For example, authors Duggirala et al. (2022) estimate the proportion of female and male astronauts over time based on historical numbers going back to the 1960's. The authors do so by collecting counts of all astronauts that went into space by gender since the 1960's and using it to regress to a best-fit logistic curve that was used to estimate future trajectories of both female and male astronauts (Duggirala et al., 2022). Similarly, I may test logistic curve models for kidney and renal pelvis cancer survival as an alternative to Moore's law models.

Similar to space satellites, authors Greene et al. (2023) focus on predicting the scrappage rates, or lifetime of the automobile product as a function of vehicle age. Using historical data, the authors find that modified logistic functions fit the historical data better than a Weibull analysis. This data helps analyze the benefits and costs of policies such as promoting deep decarbonization, energy efficiency, reduced pollutant emissions and vehicle safety (Greene et al., 2023).

Survival Prediction in the Healthcare Domain

Authors Alexopoulos et al. (2022) use historical data to help predict survival rates of glioblastomas multiforme, which is of interest, particularly with its increase in incidence rates over the past few decades. Using the multivariate Cox proportional hazards regression and accelerated failure time lognormal regression, the latter was found to be the better model to describe the survival patterns for glioblastomas multiforme patients. It was also noteworthy that the authors suggested that demographics such as gender and race were not useful as predictors based on their findings (Alexopoulos et al., 2022).

In the area of heart failure, Levy et al. (2006) developed a multivariate risk model to predict 1-, 2-, and 3-year survival in heart failure patients. Using the multivariate Cox model, the authors were able to predict prognosis in 1125 patients depending on whether mediations or devices were added to each patient's regimen. The method was found to be very useful, however it is important to note that the prognoses of heart failure is about 50% for the first 5 years from diagnosis while the 10-year prognosis is at about 35% (Jones et al., 2017). On the other hand, the 5 year survival rate for kidney cancer is about 77% (American Society of Clinical Oncology, 2023). This stark difference is important to note, as it means that heart failure data will place more weight on recent data due to its generally shorter prognosis, while kidney cancer would tend to rely more on historical data.

Pocock et al. (2013) also attempted to derive a risk score for heart failure patient mortality. This was done using a meta-analysis of almost 40,000 heart failure patients that were globally located within 30 cohort studies. The authors utilized multivariable piecewise Poisson regression with stepwise variable selection to determine a predictive model. Although the authors found similar findings within cohorts, there were various discrepancies between the cohorts. The authors suspect this may be due to the geographical variation and patient selection criteria of the studies. In summary, the findings allow for generalizability but do not help predict individual patient outcomes.

For kidney cancer in particular, various studies have been conducted. These studies specifically pertain to the numerous variables to consider when predicting kidney cancer. The first set of variables are therapeutics. In other words, survival estimates may be based on different treatment plans. Kidney cancer treatment may include various interventions such as surgery, ablation, targeted therapy, and clinical trials to name a few (National Comprehensive

Cancer Network, 2023). Care plan recommendations will vary based on various factors including age, cancer stage, cancer location, etc. Note that the Tumor, Node, Metastasis (TNM) staging system is commonly used as an industry standard to classify the extent of spread of malignant tumors (Brierley et al., 2017).

Hollingsworth et al. (2007) explore five-year survival rates after surgical treatment of over 25,000 kidney cancer patients using SEER data from various United States cancer registries. The authors found that patients with smaller kidney tumor masses had lower cancer-specific mortality. However, they also noticed that competing-cause mortality rose as patient age increased despite surgical therapy. It is important to note that 81% of participants in this study were white, and only 38% were women.

Jiang et al. (2022) on the other hand examine integrating various patient genetic data and determining patient survival based on drug therapy. They also only focus on a very specific type of cancer, clear cell renal cell carcinoma. Utilizing this personalized treatment data, the authors were able to explore data from a cohort of 258 patients. Using machine learning, a variety of clustering algorithms were utilized to integrate multiple genetic profiles at the same time to perform a classification study on renal cell carcinoma patients into two genetic groups of patients and build an effective model that predicts survival rates. The authors found both the training and validation sets to be good survival predictors for renal cell carcinoma patients.

Zhang et al. (2020) conducted a similar study on clear cell renal cell carcinoma survival prediction, however they worked with publicly available genetic data from the Genomic Data Commons Data Portal (National Cancer Institute, n.d.(b)) and the Cancer Genome Atlas (TCGA) (National Center for Biotechnology Information, n.d.). Using this data as well as other clinical prognostic parameters, they developed a gene-based predictive model for the survival of clear

cell renal cell carcinoma patients by incorporating multiple prognostic-related genes and clinical parameters. They did so by examining sequence data from TCGA to identify differentially expressed genes. The selection process involved utilizing univariate Cox proportional hazards regression analysis, the Least Absolute Shrinkage and Selection Operator method (LASSO), and best subset regression (BSR). Ultimately, a five-gene group with the lowest Akaike Information Criterion (AIC) value was identified through this screening process. Considering that the authors only explored public data, there are potentially additional genes or non-publicly available variables that could be explored.

Similar to the two studies above, authors Cheng et al. (2017) also investigated clear cell renal cell carcinoma. The key difference of this study is that the authors used histopathologic images that help diagnose and stage kidney cancer for survival prediction. Specifically, they investigated these diagnostics along with genomic data of 410 patients from the publicly available Cancer Genome Atlas data. By utilizing the power of machine learning, the authors used a combination of quantitative morphologic features extracted from tissue images and gene expression signatures to predict survival outcomes of clear cell renal cell carcinoma patients. The authors noted that prediction using both images and genetics was more powerful than using each separately. It is important to note that almost 66% of participants were male, and most patients were in stage I of the disease. It is becoming clear that researchers continue to focus their efforts in the field of genomics for personalized medicine.

Brenner & Hakulinen (2006) reviewed the progress of cancer patient survival rates. Noting the criticality of survival data being as current as possible, the authors suggested conducting a period analysis to help accomplish this. They noted however, that although period analysis helps provide the most recent data on cancer patient survival, accuracy may be lost in

the process as a trade-off. To account for this, the authors proposed using a model-based approach that utilizes recent data while losing minimal precision. This approach was tested on patients from Finland that had 1 of 20 different cancer types between 1953 and 2002. They found the model-based approach to be more precise compared to conventional period estimate data (Brenner & Hakulinen, 2006).

Technological Innovation

Burg & Ausubel (2021) consolidate and analyze Intel processor characteristics from 1959 to 2013 and reveal a pattern consistent with a biphasic sigmoidal curve, demonstrating characteristic periods of 9.5 years. These periods are marked by significant increases in transistor density, about a tenfold surge in around six years, followed by nearly three years of minimal growth rates. These six waves of density increase provide crucial insights into the mechanisms driving processor advancements, shedding light on potential future limits that could be surpassed (Burg & Ausubel, 2021). This is novel as they assert gradual advancements, accumulated step by step, align with an overarching exponential trend. These incremental steps collectively contribute to generating a pattern of continuous improvement over an extended period. For instance, a stepwise analysis can demonstrate the evolution of transistor density, showcasing how successive incremental advancements ultimately lead to exponential growth in transistor capacity.

Modis (2002) attempted to address instances of punctuated equilibrium despite the isolated episodes of rapid evolution between long periods of little or no change. He did so by analyzing 13 different evolutionary points and derived future predictions by applying exponential and logistic models to the data. The logistic model was found to be a better predictor and suggests that the maximum growth rate for complexity has already been reached. Furthermore, it anticipates a decline in the rate of change for complexity (and consequently, in our lives) in the

future. One implication is that we are approximately halfway through the universe's lifespan. Additionally, the high present level of complexity's growth rate has evolved through seven subprocesses, which can themselves be described using logistic models (Modis, 2002).

Regardless, today there are various indicators to quantitatively investigate historical dynamics or trends (Turchin, 2018). Authors Arthur & Polak (2006) write about modeling technological evolution within a simplified artificial system. Their paper investigates how technology, consisting of devices and methods, evolves through the creation of new elements from existing ones, forming a network of interconnected components that give rise to novel technologies. The focus of their study is on logic circuits as the elements within this system, with new elements generated through combinations of simpler components. The primary importance of this advance lies in its ability to shed light on the underlying mechanisms of technological innovation. It underscores the crucial role of simpler elements as building blocks for the development of complex technologies, paralleling the concept observed in biological evolution.

Authors Nagy et al. (2013) tested various hypotheses for predicting technological improvement. It evaluates the performance of six postulated laws, including Wright's law, Moore’s law, and others, to forecast the future costs of 62 different technologies using an extensive database. The findings indicate that technological progress is indeed forecastable, with the forecasting error growing linearly with the forecasting horizon. This has far-reaching implications for engineers, policymakers, and private investors, enhancing their ability to make informed decisions about technological investments and resource allocation (Nagy et al., 2013).

The importance of this paper is found in its potential to inform technology-related decision-making and policy development. It offers a systematic approach to evaluating and comparing the effectiveness of different forecasting models, guiding strategies for innovation,

and resource allocation. The discovery of the exponential increase in production and the predictable nature of technological progress can influence decisions related to climate change mitigation, technological investments, and long-term planning in various domains. The paper prompts important questions for future research, particularly in terms of exploring the underlying mechanisms behind the regularities observed in technological improvement and examining the adaptability of these models to different technological and environmental contexts (Nagy et al., 2013).

On the other hand, authors Solé et al. (2014) investigate the dynamics of technological innovation and the conditions under which it may lead to explosive growth or enter a linear regime. They develop a generalized model of technological evolution, focusing on two crucial properties: the number of previous technologies required to create new innovations and the rate at which technology ages. The study explores two different models of combinatorial growth, one involving long-range memory and the availability of old inventions for new innovations, and the other with aging having a characteristic time scale.

The researchers conclude that under specific conditions, technological singularities can emerge, representing a period of rapid innovation, while under different conditions, a "black hole" of old innovations appears and expands over time, slowing down the rate of invention creation into a linear regime. These findings offer valuable insights into the factors influencing technological progress, with implications for research, policy, and business strategies (Solé et al., 2014).

The findings in this paper are novel in that it provides a structured framework for understanding when technology may experience explosive innovation or enter a period of slower progress, helping researchers, policymakers, and businesses make informed choices. The models

developed in this study can serve as valuable tools for understanding the dynamics of technological evolution and the conditions under which innovation reaches critical points. The paper raises important questions for future research, particularly in exploring the specific factors that determine when technological innovation follows an explosive path or enters a linear regime. Researchers may delve into the impact of external variables, such as economic, social, or policy factors, on the trajectory of technological evolution. Additionally, future studies could investigate the long-term consequences of technological singularities and "black holes" on various industries and economies and explore strategies to navigate or mitigate their effects. While the study's focus is primarily theoretical, further research could explore the practical application of these findings in real-world decision-making and strategy development, extending their relevance beyond theoretical models to practical contexts (Solé et al., 2014).

Similarly, Basnet & Magee (2016a) introduce a significant advance in our understanding of technological improvement rates by empirically confirming the relationship between these rates and artifact interactions in various domains. Prior quantitative models had posited that the pace of technological advancement is inversely proportional to the level of artifact interactions, suggesting that more complex domains with a higher number of interactions tend to exhibit slower improvement rates.

This paper provides empirical evidence supporting these modeling predictions, effectively validating the importance of considering artifact interactions in the context of technology development. This insight is of paramount importance as it not only verifies existing models but also emphasizes the significance of addressing complexity and interaction dynamics in various technological domains. It offers valuable guidance for decision-making, resource

allocation, and strategy development in industries where technological progress plays a pivotal role (Basnet & Magee, 2016a).

From this research, important questions emerge for future investigations, including a closer examination of the mechanisms by which artifact interactions influence improvement rates and whether these findings are adaptable to a wide range of technological and industrial contexts. Furthermore, there is room for exploring strategies to manage and optimize improvement rates while handling increased complexity, which would have practical implications for multiple sectors dealing with technological advancement. While the paper doesn't delve deeply into the practical approaches for addressing high artifact interactions, it paves the way for further research in this direction (Basnet & Magee, 2016a).

In another paper published the same year, both authors (Basnet & Magee, 2016b) attempt to understand the dynamics of technological innovation across various domains by presenting a simple model. This model is built on the foundation of inventive design processes and probabilistic analogical transfers, proposing that inventive design results from combining existing knowledge and individual operational ideas to generate novel concepts. The model attributes varying rates of technological improvement in different domains to differences in interactions among components and scaling laws, while the exponential behavior is attributed to the analogic transfer process.

This knowledge is essential as it offers a systematic framework for comprehending the factors influencing technological advancement. It provides a rationale for why certain domains progress at faster rates than others and highlights the central role of inventive design and analogical thinking in shaping technological innovation. The model's application can inform

strategies for optimizing technological improvement and innovation management in diverse fields (Basnet & Magee, 2016b).

From this paper, important questions emerge for future research, including a deeper exploration of the mechanisms driving the analogical transfer and inventive design processes. Researchers might also investigate practical implications for managing and enhancing technological innovation rates in various domains. Furthermore, empirical validation of the model's predictions and assumptions is needed to assess its real-world applicability. While the paper forms the basis for understanding technological advancement, further research could delve into practical strategies and case studies to illustrate the model's application. The paper's novelty lies in the structured model it provides to explain the variations in technological advancement rates. While the concept of inventive design and analogical thinking in technology development is not new, this model offers a systematic framework for comprehending the role of these processes in shaping innovation dynamics (Basnet & Magee, 2016b).

In an alternative analysis, authors Magee et al. (2016) investigate technological change and performance trends over time. Specifically, they focus on the relationships between time, effort variables such as cumulative production, research and development (R&D) spending, patent production, and the performance of technology in various domains. The paper verifies Sahal's equation (Sahal, 1979) for additional effort variables, extending its applicability to patent and revenue data beyond cumulative production. The findings emphasize the accuracy of Sahal's equation when all three key relationships are well-fitted, which involve exponential links between performance and time, effort and time, and a power law connection between performance and effort variables (Magee et al., 2016).

This research is crucial for gaining deeper insights into research and development management, technological forecasting, and strategic decision-making. It offers valuable tools for industries, policymakers, and researchers to forecast and optimize technological change, guiding resource allocation in research and development. It also equips decision-makers and researchers with a structured framework for understanding and predicting technological progress which is essential for various domains (Magee et al., 2016). Perhaps unsurprisingly, at the 2017 Association for Computing Machinery meeting, researchers Denning & Lewis (2016) indicated that not only is growth of computing exponential, but they hypothesize that it is one small component of the growth of a planetary computing ecosystem.

In 2019, Axtell et al. attempted to develop a simple yet robust model that simulates the evolution of economic goods and technological progress. This model characterizes the dynamics of goods and technology as the outcome of a stochastic process driven by purposive agents in a large population. It considers the introduction of new goods through the recombination of existing ones, with agents evaluating and adopting these goods based on their perceived value. The model highlights several key properties, including the transient nature of the population of goods, the variability in the total number of goods over time, increasing agent welfare, and the cyclical pattern of technological stasis followed by bursts of technological progress. The model's ability to quantitatively capture many qualitative ideas about technological evolution makes it a valuable tool for analyzing and predicting trends in technological progress. It offers insights into the complex interplay between invention, adoption, and competition within an economy. However, the application of this model to real-world economic and technological systems is needed (Axtell et al., 2019).

Tsai et al. (2023) systematically review various methods that may be utilized to extrapolate future trends from data. Their research classifies the methods used in existing studies, highlighting the continued popularity of traditional growth curves and time series methods, as well as the emergence of newer machine learning-based hybrid models. The paper's value lies in its potential to inform and guide technology forecasting practices, encouraging a shift towards more contemporary techniques, and stimulating further research to assess the superiority of these methods. The focus of this paper on evolving forecasting approaches has broader implications for research methodology, potentially improving predictive modeling in various scientific domains, including medical research. Further research questions could revolve around the conditions under which each forecasting method is most suitable and the development of standardized practices in the field (Tsai et al., 2023).

Gams & Kolenik (2021) explore the relationship between the information society, electronics, and artificial intelligence (AI). They do so by reviewing various ways that describe how these three are all connected. These demonstrate how fast electronics and AI are improving. For example, they talk about how devices are getting better and cheaper very quickly, and how people are using them more and more. The authors point out that although there are some signs that rate of growth might decline, there are still various ways to make electronics and AI even better. The authors mention how AI is already doing things that were thought to be impossible at one point, like recognizing things in the real world better than humans. AI is also improving at tasks such as creating art and writing computer programs. In summary, although technology is growing rapidly and AI is a big part of that, there is a limit to any progress, generally following an S-curve due to saturation (Gams & Kolenik, 2021).

An important study conducted by authors Basnet and Magee (2017) explores the development of a novel patent-based method to empirically study the influence of artifact interactions on the improvement rates of various technological domains. The study identifies specific keywords within patent content that signal artifact interactions, enabling a technology domain-agnostic and cost-effective approach to quantifying these interactions. This is important due on the study's potential to shed light on why some technologies improve faster than others. It offers empirical evidence supporting the previously proposed model that suggests the improvement rate for a domain is proportional to the inverse of the domain's interaction parameter (Basnet & Magee, 2017).

While the concept of artifact interactions as a determinant of improvement rates has been proposed in quantitative modeling research, this paper offers a unique, patent-based approach that is both domain-agnostic and cost-effective. It does so by bridging the gap between theoretical models and empirical evidence in the field of technological progress. Understanding the role of artifact interactions in technological progress can inform strategies for enhancing innovation and development in different domains (Basnet & Magee, 2017).

Kidney Cancer Survival Prediction

In recent years, there are indications that the global incidence of kidney cancer, which had been steadily rising for over two decades, has begun to stabilize or even decrease (Motzer et al., 2022). Kidney cancer in adults comprises two primary types: renal cell carcinoma (RCC), which is the predominant form, and renal transitional cell carcinoma (RTCC), typically originating in the renal parenchyma and renal pelvis, respectively (Chow et al., 2010). While the temporal trends of kidney cancer types worldwide are not well-established, the incidence of RCC in the United States has continued to increase, particularly for early-stage tumors (Capitanio et

al., 2018) . On the other hand, the incidence of RTCC has declined, and overall kidney cancer mortality rates have plateaued. Similar trends of stabilized kidney cancer mortality rates have also been observed in Europe (Chow et al., 2010).

In 2006, authors Weiss and Lin provided an overview of the current state of kidney cancer diagnosis, therapy, and the emerging novel treatments that capitalize on newly elucidated molecular pathways associated with kidney cancer oncogenesis. The authors mention that despite having a significant understanding of its genetic underpinnings and the identification of critical signaling pathways, kidney cancer has experienced a continuous increase in both the number of new cases and the rate of death over the past few decades (Weiss & Lin, 2006).

As of the year 2006, although the there were fewer than 200,000 new diagnoses in the United States (US), it was considered the sixth leading cause of cancer death in the US accounting for up to 11,000 deaths per year (Weiss & Lin, 2006). Approximately 90% of all kidney cancers are renal cell carcinomas. Within the renal cell carcinoma cancer type, there are various subtypes of cancer, the most common subtype affecting individuals being clear-cell renal cell carcinoma (Ljungberg et al., 2011).

Clear-cell renal cell carcinoma is a subtype of kidney cancer located in the renal tubules that filter waste from blood (Cleveland Clinic, 2022). For this reason, most kidney cancer research efforts are focused on clear-cell renal cell carcinoma as it represents 75% of all kidney cancer cases. 5-year survival of patients with localized disease is 89%, in regionally advanced disease 61% and in metastatic disease an alarming 9% (Weiss & Lin, 2006). The incidence of kidney cancers has been increasing at a rate of about 2% per year for the past 30 years (Ries et al., 2006). Demographically, male African-Americans were impacted the most by this disease (Weiss & Lin, 2006). Authors Wallen et al. (2007) noted that rates were increasing more rapidly

in the black than in the white population and survival was worse for black individuals at all stages of diagnosis (Wallen et al., 2007).

Michael et al. (2022) investigated if there was a trend among histologic subtypes on the overall survival of patients with renal cell carcinoma who have undergone renal mass biopsy. Their findings suggest that relying on histology obtained through renal mass biopsy may have limited utility in predicting survival although they raise important questions for future research, such as whether there are other clinical contexts where histologic subtypes may play a more crucial role in prognosis, and whether there are specific patient populations that would benefit from a more nuanced approach to kidney cancer management (Michael et al., 2022). Tilki et al., (2014) had similar conclusions pertaining to kidney cancer subtypes.

Kidney cancer may be treated using surgical and non-surgical approaches. Non-surgical approaches include targeted therapy, immunotherapy, radiation therapy, ablation, and clinical trials. Despite surgery being the primary treatment for kidney cancer, the recommended treatment protocol depends on the stage of the cancer, the patient's overall health, and other factors (National Comprehensive Cancer Network, 2023). Protocols and recommendations continue to get updated. For example, studies have shown improved survival with partial nephrectomy compared to radical nephrectomy. This outcome is typically due to the prevention of morbidity and mortality associated with chronic kidney disease from a radical nephrectomy (Tan et al., 2012). Regardless, it is essential for patients to discuss their options with their healthcare team to make informed decisions about the most suitable treatment plan for their individual case (National Comprehensive Cancer Network, 2023).

Although the overall mortality rate from kidney cancers has increased slightly since the 1970s, the increase is not as rapid as the incidence rate. This discrepancy is due to a significant

improvement in 5-year survival (Kosary & McLaughlin, 1993). Up to 70% of individuals diagnosed with small clear-cell renal cell carcinoma tumors survive for five years following their initial diagnosis. However, treatment is less successful when dealing with larger tumors or cancer that has spread to other parts of the body. In such instances, the five-year survival rates may decrease significantly to approximately 10%. When patients present with advanced disease, they have only an 18% two-year survival rate (Linehan et al., 2003). Many additional factors impact prognosis including tumor location, size and number of tumors (Cleveland Clinic, 2022).

Although the five-year survival rate for kidney cancer has improved, the incidence has risen, while the mortality rate remains unchanged. See Moore's law and Survival Estimations for differences between survival and mortality. This trend indicates increased diagnoses resulting from enhanced early detection, contributing to a higher overall cancer burden (Cho et al., 2014). As the US population ages and the prevalence of risk factors such as obesity and hypertension increase, the burden of disease will increase significantly. This is a great concern as the US's total expenditure for kidney cancer was $400 million in the year 2000, and continues to grow (Wallen et al., 2007).

It is difficult to discuss cancer survival prediction without mentioning the Gompertzian model. Devised by mathematician Benjamin Gompertz in 1825, the model originally served as a framework to explain human mortality rates, but was later adapted to characterize tumor growth patterns (Tu, 2010). Gompertz's equation implies that as a tumor grows rapidly (exponentially), and approaches the maximum size the environment can support, the growth rate decreases. His model also operates under the assumptions below (Laird, 1969):

1. Initially, tumor growth follows an exponential trend but gradually decelerates as time progresses.

2. The rate of tumor growth is directly proportional to the tumor's current size (with caveats #1 and #3).
3. There exists a maximum capacity or limit to the tumor's growth, beyond which it cannot expand further.

Over 100 years later, Laird challenged these assumptions after conducting a literature review and concluding that true exponential growth of tumors is rare and typically occurs for only brief periods. Instead, most tumors exhibit a continuous deceleration in growth as they enlarge. When plotted against time, this results in a curve that closely approximates a straight line, particularly when the diameter of a solid tumor or the cube root of total cell number in an ascites tumor, also called a fluid filled tumor, is plotted against time (Laird, 1969). Ten years later, Goldie and Coldman, (1979) described cell heterogeneity and the emergence of resistance to treatments employed during cancer therapy. They hypothesized that within the diverse population of cancer cells, minute fraction inherently possess resistance to chemotherapy or other anti-cancer treatments. As a result, the resistant cells proliferate and repopulate the tumor, leading to relapse or recurrence of the cancer that is now more resistant to the initial treatment (Kow, 2023). This concept eventually became recognized as the Goldie-Coldman principle. The hypothesis highlights the challenges in eradicating all cancer cells using conventional treatments and emphasizes the need for developing new therapeutic strategies capable of specifically targeting and eradicating these resistant cell populations (Naozuka et al., 2022). As a result, the hypothesis has contributed to scientists' comprehension of mechanisms by which cancer cells undergo evolution, adaptation, and acquire resistance to treatment, prompting researchers to investigate combined therapeutic regimens, personalized medicine, and pioneering treatment methodologies aimed at overcoming drug resistance and improving cancer outcomes. Similar to the

Gompertzian model, this hypothesis focuses on the characterization of individual tumor growth pattern, unlike a population statistic such as cancer survival.

Relevant Equations

Exponential Curves

An exponential curve describes the phenomena where a quantity grows or decays at a constant percentage rate over time or as a function of another variable (Denning & Lewis, 2016). Although they may be leveraged in various fields such as science, mathematics, and engineering, exponential growth is frequently observed in technological advancements (Berleant et al., 2021). Particularly in this case, we attempt to curve fit survival time data. Doing so will allow research to determine parameter values of a function which in turn can make predictions for time points for which data are not available, as well as to summarize relationships between variables (Arlinghaus, 1994). In order to fit our data into an exponential curve, we begin with a simple equation to represent such an exponential curve denoted as (Bartlett, 1976):

$$\boldsymbol{y = 2^{x}} \qquad (1)$$

Since we are referring to Moore's law, and interested in exponential growth, we need to take doubling time into consideration. According to Moore, for chips, this would be every two years, however depending on the data set and domain this value might be different. To represent this, we use the formula below:

$$\boldsymbol{y = C * 2^{((t-t_0)/D)}} \qquad (2)$$

where $\boldsymbol{t}$ and $\boldsymbol{D}$ are function parameters. The input value $\boldsymbol{t}$ represents start year, which could be year of diagnosis, year of manufacture of a spacecraft or other artifact, etc.

The value $\boldsymbol{y}$ is expected (average) survival time of an individual. The reference year (in essence, where we would draw the y-axis) is $\boldsymbol{t_0}$, and $\boldsymbol{C}$ is the survival time for that year. Any year could be

chosen for t_0 so a year should be chosen that is convenient and results in a convenient value of C (which is, in essence, the y-axis intercept value, or the estimated survival time for whatever year t_0 was chosen for the y axis). In order to find the ideal values for parameters C and D, regression can involve initially guessing estimates for them, and then repeatedly adjusting them in a search for their optimized values. The optimal values are the ones that produce the lowest sum of squares error when comparing the curve to the data we are fitting to the curve (Berleant et al., 2021). Rather than regress eq. (2), however, below we will convert eq. (2) to a closely related curve. But first, we re-write equation (2), to better suit the domain of interest, as a function where survival time, s_x, is a function of diagnosis year, t_x:

$$s_x(t_x) = C * 2^{(t_X - t_0)/D} \qquad (3)$$

where t_x represents the date of diagnosis. The constant C still designates survival time at year t_0. This is because when, when $t_x = t_0$, then $s_x(t_x) = C$.

Recency Bias

Recency bias is a cognitive bias that refers to the tendency of individuals to give greater importance to more recent events and experiences when making judgments or decisions (Sunstein, 2019). Also known as the availability heuristic, it involves estimating the probability or frequency of an event based on how easily relevant examples or instances come to mind. In other words, people tend to judge the likelihood of an event based on how readily they can recall similar events or information from their memories (Phillips-Wren et al., 2019). The more easily something comes to mind, the more likely it is perceived to be. Key characteristics of recency bias include ease of recall, media influence, personal experience, and confirmation bias (Hintzman, 1992).

Lifetime prediction data often relies on historical information to make projections about future events, and recency bias can distort these predictions in several ways (De Caigny et al., 2020). When making life predictions, people tend to give more weight to recent events or trends, assuming that they are more indicative of the future (Weber, 2006). For example, if there have been a few years of declining mortality rates, analysts might extrapolate this trend into the future, underestimating the potential for reversals or fluctuations. Recency bias can also cause individuals or models to ignore or downplay data from the more distant past. This can be problematic when trying to predict long-term trends or rare events, as historical data can provide essential context and insights, while recency bias prioritizes short-term outcomes over long-term ones (Plonsky & Erev, 2017).

It helps to implement a few techniques when trying to reduce the impact of recency bias in lifetime prediction data, and therefore increase accuracy. One of the key things to ensure is that the data set one is trying to predict includes a wide range of historical data as well as recent information. This will provide the additional context of the trends and patterns of the prediction variable. It is also important to be mindful when assigning weights to both historical and recent data. Since recent data generally carries more weight, it is important to keep historical data in mind particularly for long term predictions (Wang et al., 2016).

In the context of survival data, recency bias refers to a cognitive bias where people tend to focus more on recent or short-term survival outcomes and may underestimate the significance of longer-term or historical survival trends (Farinholt et al., 2018). When analyzing survival data for a specific disease or condition, recency bias can cause individuals to place a disproportionate emphasis on the survival rates of patients in recent years, possibly leading to the perception that there have been more significant improvements or deteriorations in survival than there actually

have been over a longer time frame (van Gerven et al., 2008). This bias can be problematic in situations where medical treatments or interventions take time to show their full effects, as it may lead to premature conclusions about the effectiveness of certain treatments or interventions (Gwilliam et al., 2013). To mitigate recency bias in survival data analysis, it's important to consider long-term trends and outcomes, ensuring that the evaluation of survival rates is not overly influenced by recent data but takes into account the complete historical context (Strauss et al., 2006).

In their 1996 paper, authors Brenner and Gefeller (1996) address the issues of recency bias and the lack of recent historical data by introducing the period monitoring methodology for estimating long-term survival rates in cancer patients. In perhaps the first account of period analysis under that name, (Brenner & Gefeller, 1997) describe the method, compare it to traditional cohort analysis (National Cancer Institute, n.d.(a)), and explain how to apply it with both a suitably modified traditional life table calculation method and, alternatively, a suitably modified Kaplan-Meier calculation method. This article explains the approach at a relatively detailed and basic level that may make it more understandable to many readers. An even earlier account by the authors (1996) provides a detailed description of how their method (which they call "period monitoring" in that article) gives improved lifetime estimates compared to the traditional cohort analysis approach when treatment is improving over time leading to improving survival times. Later renamed period analysis, this methodology offers a more up-to-date approach to estimating long-term survival rates than utilizing standard survival analysis techniques (Brenner & Gefeller, 1997).

This is important as it introduces an alternative to traditional long-term survival statistics, which rely on cohort-based analysis, often becoming outdated as they reflect the survival

expectations of patients diagnosed many years ago. The authors test period analysis performance by comparing survival estimates obtained through period analysis with those obtained through traditional survival analysis for a specific calendar period and examines how well they align with the actual observed survival rates for patients diagnosed with cancer during that period. This was done using the Finnish Cancer Registry data, analyzing various variables to test the reliability of period analysis (Brenner et al., 2004).

The authors initially found that period analysis was advantageous compared to traditional cohort analyses across all age groups. However, they also observed that the survival rates were most improved for childhood cancers. Upon further analysis of the 15 most prevalent cancer types in Finland and major childhood cancers in the United States, the researchers found similar trends. In most cases, improvements in survival rates over time were evident, except for certain cancers like pancreatic and lung cancer, where no significant improvements were observed. Notably, when considering 20-year survival curves, period analysis demonstrated even more advantages over traditional cohort-based analysis compared to 10-year survival curves for the most common cancer types (Brenner et al., 2004).

In a similar paper published 2 years later, authors Brenner and Hakulinen (2006a) used the same Finnish Cancer Registry data to analyze the performance of period analysis. The authors found that period analysis consistently excelled in cases where cancer prognosis significantly improved over time. In contrast, traditional methods showed superior performance for cancers with persistently poor and minimally improving prognoses, such as esophagus, lung, liver, and pancreatic cancers. Clearly, this methodology can be applied not only to kidney cancer but also to a wide range of cancer types aiding in better understanding the course of cancer, evaluating treatment outcomes, and making informed decisions in the management of cancer

patients, contributing to the overall goals of improving cancer survival rates and patient care (Brenner & Hakulinen, 2006).

Recency Bias in Exponential Curves

While equation 3 currently predicts kidney and renal pelvis cancer survival time using the diagnosis date, denoted as $\boldsymbol{t_x}$, as the independent variable, an objective is to mitigate recency bias. To achieve this, we aim to derive an alternative equation from equation 3, which models survival time based on a different but related independent variable, the year of death $\boldsymbol{t_d}$. Subsequently, we intend to conduct a regression analysis on this new equation to accurately represent a dataset comprising ordered pairs of (*death year*, *survival time*) for kidney and renal pelvis cancer survival times and, more generally, for other cancers and survival question in other domains. To obtain the desired equation the diagnosis year can be expressed as the difference between the year of death and the lifetime for any given patient (Berleant et al., in prep):

$$\boldsymbol{t_x = t_d - s_d(t_d)} \qquad (4)$$

where $\boldsymbol{t_d}$ is the independent variable and $\boldsymbol{s_d(t_d)}$ is a model predicting expected survival time as a function of year of death. Their difference is a prediction for diagnosis year $\boldsymbol{t_x}$. Note that $\boldsymbol{s_d(t_d)} = \boldsymbol{s_x(t_x)}$, since the model's survival time is the same whether the reference point is year of diagnosis, $\boldsymbol{t_x}$, or year of death $\boldsymbol{t_d}$ (Berleant et al., in prep). Using that equivalence along with equations 3 and 4 we derive a death-based prediction model:

$$\boldsymbol{s_d(t_d) = C * 2^{\frac{(t_d - s_d(t_d)) - t_0}{D}}} \qquad (5)$$

We then solve eq. (5) for the year of death, $\boldsymbol{t_d}$:

$$\boldsymbol{t_d = t_0 + s_d(t_d) + D * log2\,(s_d(t_d) / C)} \qquad (6)$$

It is convenient to set $\boldsymbol{t_0}$ to the year 1992. We then run a regression analysis on equation 6 using its parameters, $\boldsymbol{D}$ and $\boldsymbol{C}$, in order to achieve the best fit with a scatterplot of data points represented as pairs $(\boldsymbol{t_d}, \boldsymbol{s_d(t_d)})$. By leveraging the regressed (optimized) values of parameters $\boldsymbol{D}$ and $\boldsymbol{C}$, an exponential model for expected lifetime in relation to the year of diagnosis may be deduced by substituting these values for $\boldsymbol{C}$ and $\boldsymbol{D}$ in equation 3. This is novel as it allows us to predict current and relevant survival times while accounting for recency bias. Currently, for a 10-year survival period, patients diagnosed more recently than 10 years ago would be excluded from calculating $\boldsymbol{s_x}$ (since diagnosis date $\boldsymbol{x}$ is more recent than 10 years ago), but they would be included in calculating $\boldsymbol{s_d}$. Thus, using $\boldsymbol{s_d}$ allows using more data points.

We have been modeling lifetime as an exponential function of diagnosis date. Why not model it as an exponentially increasing function of death date? This turns out to be impossible. The conundrum of doing so is that as the increase in lifetime occurs at a faster and faster rate, at some point this forces the diagnosis year to become earlier and earlier over time, causing a reductio ad absurdum. A better predictive model will need to be utilized.

Doubling Time	Death Year	Dx. Year	Avg Lifetime
2 years	2010	2009.75	0.25
2 years	2012	2011.50	0.50
2 years	2014	2013.00	1.00
2 years	2016	2014.00	2.00
2 years	2018	2014.00	4.00
2 years	2020	**2012.00**	8.00

Table 1: Hypothetical Example of the Reductio Ad Absurdum Problem

Table 1 demonstrates a hypothetical example serving as a thought experiment using death year to calculate survival times. Looking at the figure, we see the average death in 2020 was diagnosed before the average death in 2018! This illustrates the strange situation that must eventually occur for any exponential increase in lifetime as a function of death year.

Relevant Resources

Surveillance, Epidemiology, and End Results (SEER)

Background

The Surveillance, Epidemiology and End Results (SEER) program is a comprehensive cancer surveillance system in the United States. It is managed by the National Cancer Institute (NCI), a division of the National Institutes of Health (NIH). SEER collects and publishes cancer incidence and survival data from various regions across the country, providing critical information for cancer research, public health planning, and policy development (National Cancer Institute, 2022a).

The SEER program was established in 1973 with the goal of monitoring and understanding the patterns of cancer incidence and survival in the U.S. population. It was initiated by the NCI to address the need for reliable and up-to-date cancer statistics to support cancer research and control efforts. Initially, SEER covered only a limited number of registries, but over the years, it expanded its coverage to include various geographic areas across the United States. The program currently encompasses 19 population-based cancer registries, covering approximately 34.6% of the U.S. population (National Cancer Institute, 2022a).

SEER collects information on all newly diagnosed cancer cases within its coverage areas, as well as data on cancer patient outcomes, such as survival rates, which provide valuable insights into the effectiveness of cancer treatments and interventions. The comprehensive data gathered by SEER supports various research studies and epidemiological analyses. Researchers use SEER data to investigate cancer trends, risk factors, treatment outcomes, and disparities in cancer incidence and survival among different populations. Its comprehensive and population-based approach ensures that the information is representative of various segments of the U.S.

population, contributing to a deeper understanding of cancer patterns and improving cancer care and outcomes nationwide (National Cancer Institute, 2022a).

Cancer-Specific Survival Estimation in SEER

To access SEER data, users must use the SEER*Stat software publicly available through the National Cancer Institute. The estimation of cancer-specific survival and the probability of death can be approached by utilizing cause of death data or expected survival tables. However, sources for cause of death information have been a subject of debate. Ideally, one would use the specific cancer type as the data source, but issues arise when cancer metastasis occurs, potentially leading to incorrect death certificate listings. In such cases, using all cancers, especially when the patient has only one cancer, may be more appropriate. Ongoing efforts aim to develop sophisticated algorithms to define data sourcing based on common metastasis sites for each cancer. (National Cancer Institute, 2022a).

There are four cancer survival estimation methods that are fairly readily supported by using SEER data. Two of the four methods are relative survival and cause-specific survival. These are both considered net survival measures. Relative survival calculates cancer survival without considering other causes of death. It compares the proportion of observed survivors among cancer patients with the proportion of expected survivors in a similar cancer-free cohort. It assumes independent competing causes of death and uses expected life tables since obtaining a cancer-free cohort is challenging. On the other hand, cause-specific survival focuses on survival from a specified cause of death while disregarding other causes. It involves specifying the cause of death, and individuals who die from causes other than those specified are considered censored. The other two cancer survival estimation methods are considered crude probability measures (National Cancer Institute, 2022a).

The first crude probability measure is crude probability of death using expected survival. This method employs expected survival data from life tables to estimate the probability of dying from other causes within each interval. Like relative survival, it assumes that cancer deaths are a minimal portion of all deaths and uses expected life tables. The other crude probability estimation method uses cause of death information. This approach calculates the probability of dying from cancer and other causes within a cohort of cancer patients, relying on cause of death information (National Cancer Institute, 2022a). *Figure 1* provides illustrations.

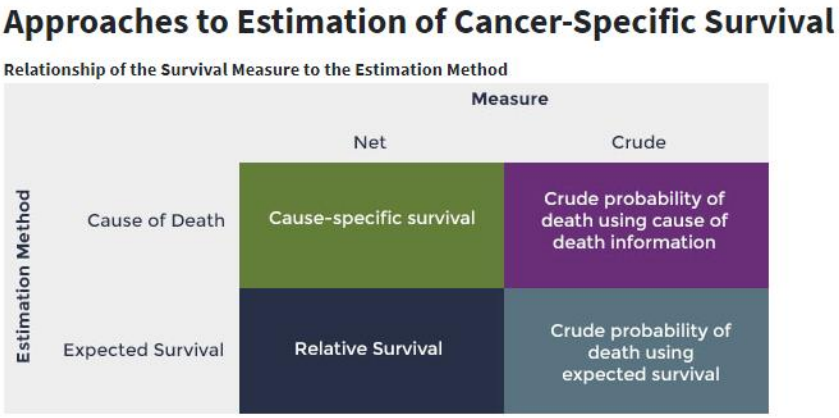


Figure 1: SEER Estimation of Cancer-Specific Survival. National Cancer Institute, 2022

The estimation methods discussed provide various perspectives on cancer survival and the likelihood of death, each with its advantages and considerations depending on the use case. Researchers must choose the most suitable approach based on their specific study and data availability. Kidney and renal pelvis cancer, as well as melanoma data may be found in this database. I was designated as an alpha and beta tester for SEER*Stat application versions 9.0.28 – 30.

The Arkansas Central Cancer Registry (ACCR)

This database, supported by funding from the National Program of Cancer Registries (NPCR) under the Centers for Disease Control and Prevention (CDC), has gathered cancer incidence data from the Arkansas residents since 1996 (Arkansas Department of Health, 2017).

The primary goal of the registry is to gather data that can be used for surveillance, research, policy interventions, and initiatives aimed at early detection and prevention (Arkansas Cancer Coalition, 2018).

In accordance with the Arkansas State Reporting Law, any organization that offers diagnostic or therapeutic services to individuals in Arkansas diagnosed with cancer is obligated to report this information to the ACCR. This reporting requirement extends to various types of healthcare facilities, such as outpatient surgery centers, hematology/oncology clinics, urology clinics, gastroenterology and dermatology clinics, hospices, nursing homes, group physician offices, and hospitals. These medical facilities are expected to submit their reports to the ACCR within six months of diagnosing and/or treating a cancer patient (Arkansas Cancer Coalition, 2018).

Arkansas Center for Health Improvement (ACHI)

The ACHI was opened in alignment with the Arkansas Health Care Payment Improvement Initiative (AHCPII). This initiative aims to transform the healthcare system in Arkansas, emphasizing a patient-centered approach that aligns with (1) improving the overall health of the population, (2) enhancing the quality, accessibility, and reliability of the patient's care experience, and (3) reducing or effectively managing healthcare costs. This comprehensive, statewide system, involving multiple payers, centers its focus on patient-centered care delivery models, prioritizing the patient's needs over a specific delivery system structure (Arkansas Center of Health Improvement, 2023).

Since 2012 the AHCPII has been spearheaded by the Arkansas Department of Human Services' Medicaid Program, with significant contributions from various and private organizations in the state. The initiative is designed to incentivize healthcare providers, including

physicians and hospitals, to deliver high-quality care to patients at a reasonable cost. In alignment with their mission, this organization houses Arkansas health data as well as Arkansas insurance claims data for research and transparency purposes (Arkansas Center of Health Improvement, 2023).

National Comprehensive Cancer Network (NCCN)

The NCCN publishes guidelines of how to treat cancer based on cancer type. It is considered the gold standard for clinical decision making (National Comprehensive Cancer Network, 2023). Pertaining to kidney and renal pelvis cancer, the NCCN provides multidisciplinary recommendations for the clinical management of patients specifically with clear cell renal cell carcinoma and nonclear cell renal cell carcinoma. These guidelines are intended to assist with clinical decision-making, but they cannot incorporate all possible clinical variations and are not intended to replace good clinical judgment or individualization of treatments. Unusual patient scenarios (presenting in <5% of patients) are not specifically discussed in these guidelines. The guidelines are reviewed and updated at least annually (Motzer et al., 2022).

The Genomic Data Commons Program

The Genomic Data Commons (GDC) is a program under the National Cancer Institute (NCI) with the goal of establishing a unified repository and knowledge base for cancer research. It supports the sharing of genomic data across various cancer studies to advance precision medicine in oncology. The GDC includes extensive data from significant cancer genomic datasets, including The Cancer Genome Atlas (TCGA) and Therapeutically Applicable Research to Generate Effective Therapies (TARGET). Notably, the GDC processes this data using consistent bioinformatics pipelines, enabling direct comparisons. Furthermore, it allows

researchers to contribute their own data, aligns it with a common reference genome, and generates high-level data such as variant calls and expression quantifications. As more researchers contribute to the GDC, it becomes an increasingly valuable tool for uncovering the molecular underpinnings of cancer, potentially leading to improved patient care (National Cancer Institute, 2023a).

The Cancer Genome Atlas

The Cancer Genome Atlas (TCGA) was a significant cancer genomics program that meticulously analyzed more than 20,000 primary cancer and matched normal samples across 33 cancer types from 2006 to 2018. With contributions from over 11,000 patients and thousands of researchers, TCGA generated an enormous dataset exceeding 2.5 petabytes, encompassing genomic, epigenomic, transcriptomic, and proteomic information. TCGA's valuable dataset is now complete, and the program is not accepting new samples for characterization. Kidney and renal pelvis cancer subtypes included in this study are clear cell renal cell carcinoma, chromophobe renal cell carcinoma, and papillary renal cell carcinoma. Melanoma subtypes studied include skin cutaneous melanoma and uveal melanoma (National Cancer Institute, 2022b).

Therapeutically Applicable Research to Generate Effective Treatments (TARGET) program

The Therapeutically Applicable Research to Generate Effective Treatments (TARGET) program is focused on employing a thorough genomic approach to identify the molecular changes responsible for childhood cancers. Its primary objective is to use this data to guide the development of safer and more effective treatments for children. TARGET operates through collaborative project teams, each dedicated to a specific disease. By comprehensively characterizing the molecular aspects of hard-to-treat childhood cancers, TARGET aims to provide valuable data to the research community, helping identify therapeutic targets and

prognostic markers and facilitating the development of innovative, improved treatment strategies for these conditions. Kidney and renal pelvis cancer subtypes included in the study are Wilms, clear cell sarcoma, and rhabdoid tumors. Myeloma subtypes are not currently included in this program (National Cancer Institute, 2022c).

3. Methods

General Methodology

Cause-specific analysis was conducted in SEER*Stat on all kidney and renal pelvis, lung and bronchus, myeloma, prostate, and breast cancer patients using November 2022 submission SEER 12 data. This dataset includes 12 registries throughout the United States and covers 12.2% of the United States population encompassing over 5 million registered cancer cases in the United States (National Cancer Institute, 2023b). Data was queried for all patients who were either diagnosed or passed away from the 5 specified cancers throughout the years 1992 to 2020.

- San Francisco-Oakland SMSA - 1992+
- Connecticut - 1992+
- Hawaii - 1992+
- Iowa - 1992+
- New Mexico - 1992+
- Seattle (Puget Sound) - 1992+
- Utah - 1992+
- Atlanta (Metropolitan) - 1992+
- San Jose-Monterey - 1992+
- Los Angeles - 1992+
- Alaska Natives - 1992+
- Rural Georgia - 1992+

Figure 2: List of 12 registries included in SEER 12 Nov Sub (1992-2020) data

To ascertain patient lifetimes, multiple variations were created based on two sets of variables. The first set of custom variables used the year of diagnosis, and went 5, 10, and 20 years out from each specified year of diagnosis. The second set of custom variables used the year

of death as an anchor. Given that our data set contained data from the years 1992 to 2020, our minimum diagnosis year was 1992, and our maximum diagnosis year was 2015. This is because any year after 2015 would not lead to complete data for even as little as a 5-year horizon. On the other hand, in this data set our minimum year of death was 1997 (the earliest year that was at least 5 years out from 1992), and the maximum year of death was 2020. This allowed us to produce the groupings in *Table 2*:

Lifetimes included in Dataset			
Survival Period		Diagnosis Year	Death Year
5 Year	Minimum	1992	1997
	Maximum	2015	2020
10 Year	Minimum	1992	2002
	Maximum	2010	2020
20 Year	Minimum	1992	2012
	Maximum	2000	2020

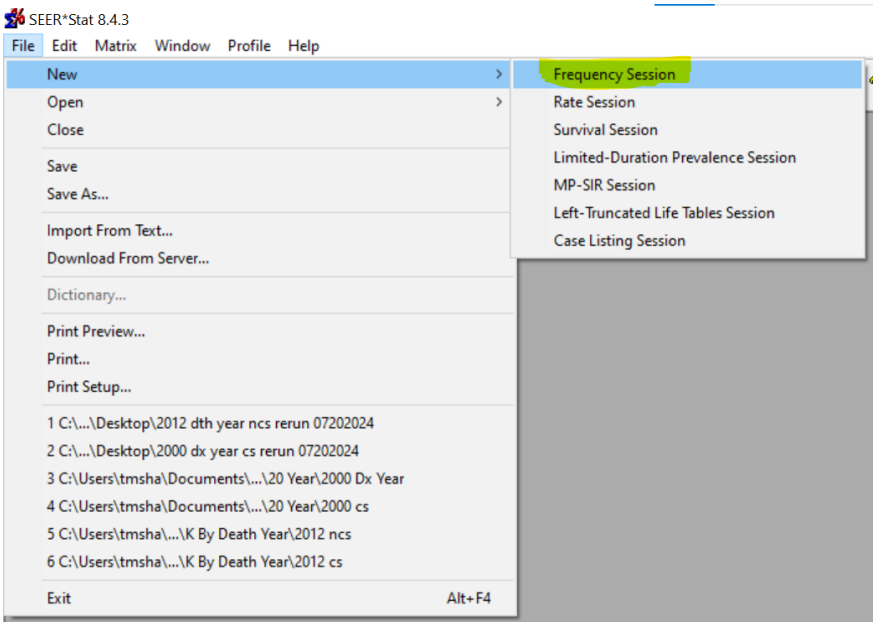
Table 2: Combinations of lifetime data years to be included in this paper

Using Microsoft Excel, data was grouped into 5-, 10-, and 20-year survival groups, and respective trends were obtained from Excel's trend analysis functionality to assess the lifetimes of kidney and renal pelvis, lung and bronchus, myeloma, prostate, and breast cancer patients who died in each death year.

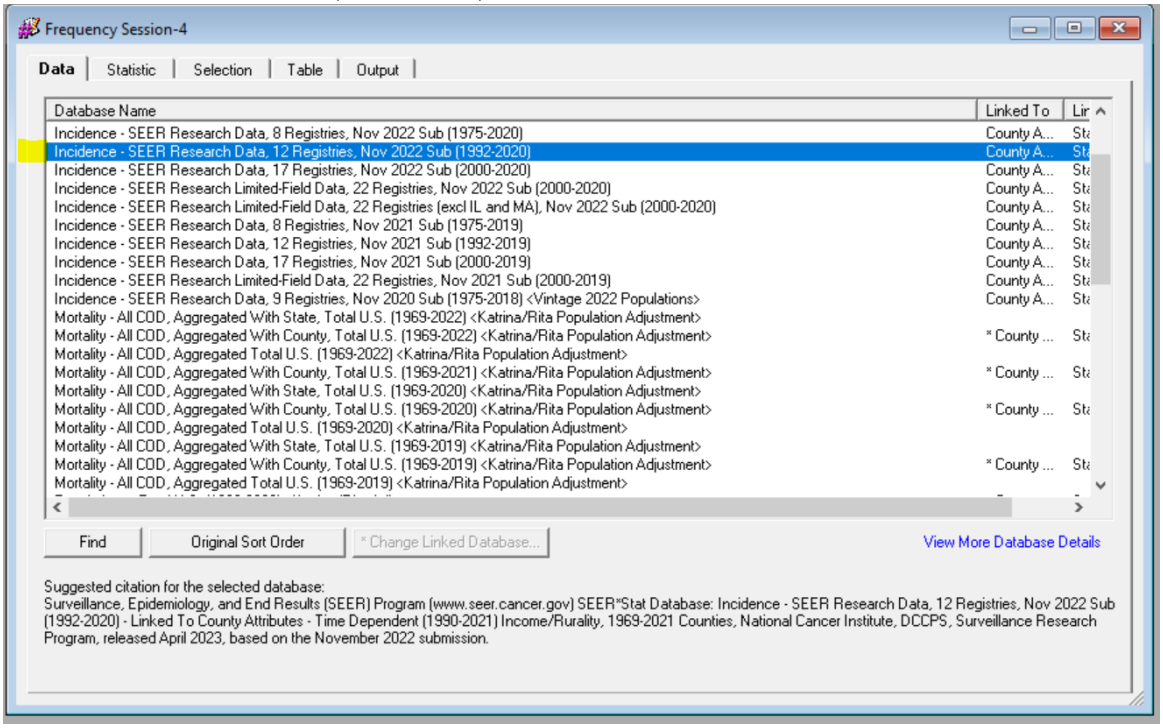
Extracting from SEER

All lifetime data was extracted from SEER for cause-specific lifetime data. Steps are as follows using SEER*Stat 8.4.3:

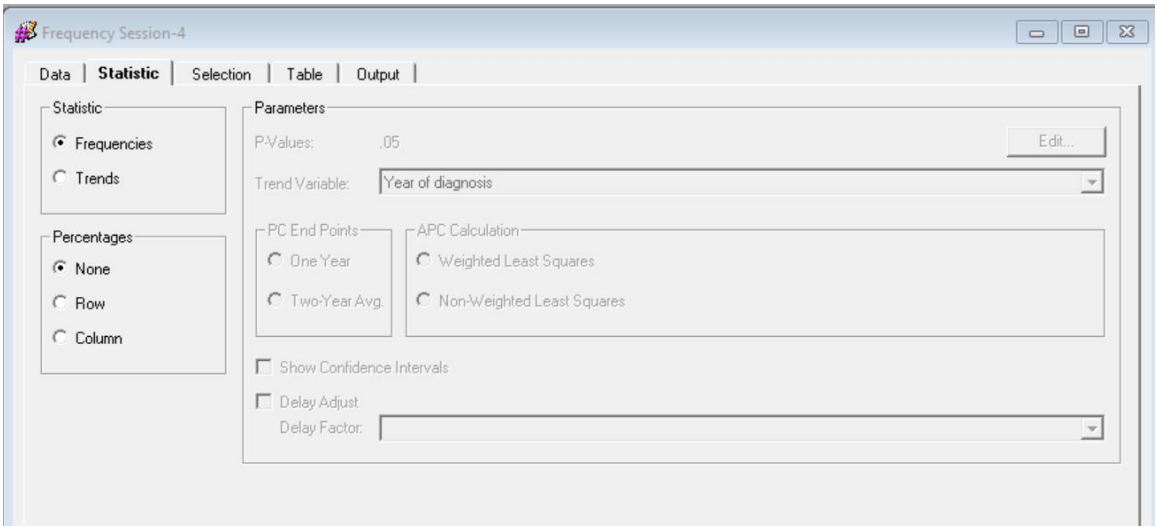
1. Create frequency session in SEER.



2. Select the Nov 2022 Sub (1992-2020) data set.

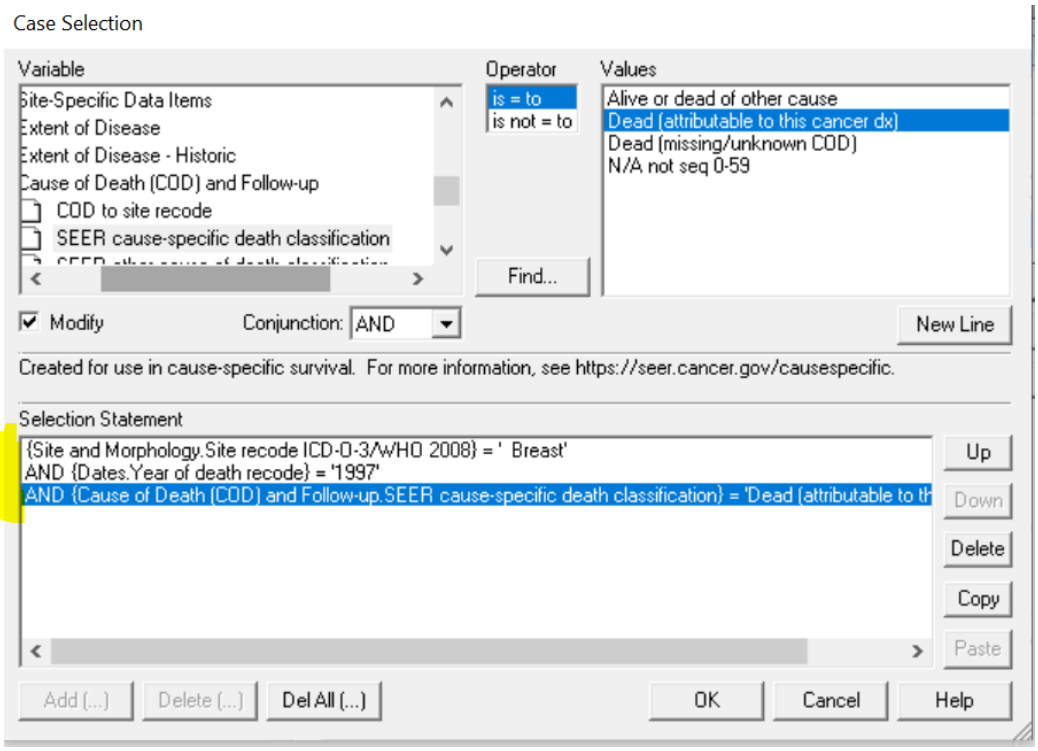


3. No changes need to be made on the ‘Statistic’ tab.

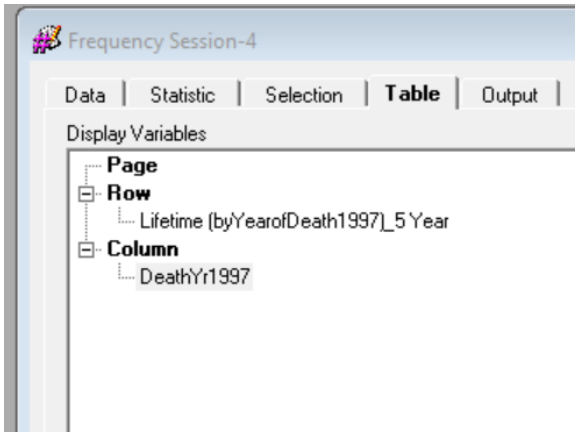


4. Under the ‘Selection’ tab, select ‘Edit’.

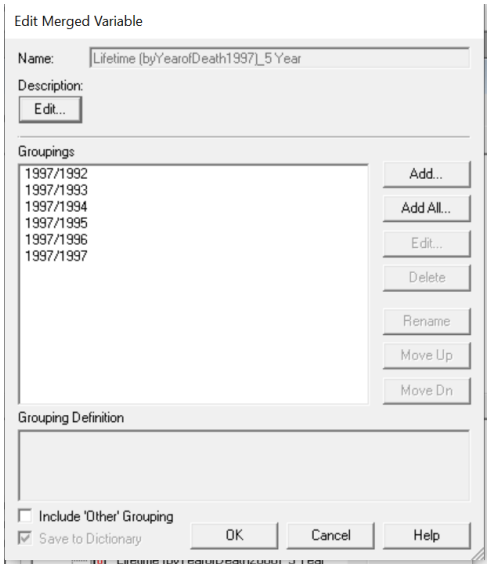
5. In this example, we want to pull the breast cancer patients that passed away specifically from breast cancer in the year 1997. To do so, the cancer type (Site and Morphology> Site recode ICD-O-3/WHO 2008), year of death of interest (Dates>Year of death recode), and cause-specific (Cause of Death (COD) and Follow-up>SEER cause-specific death classification) filters must be selected.



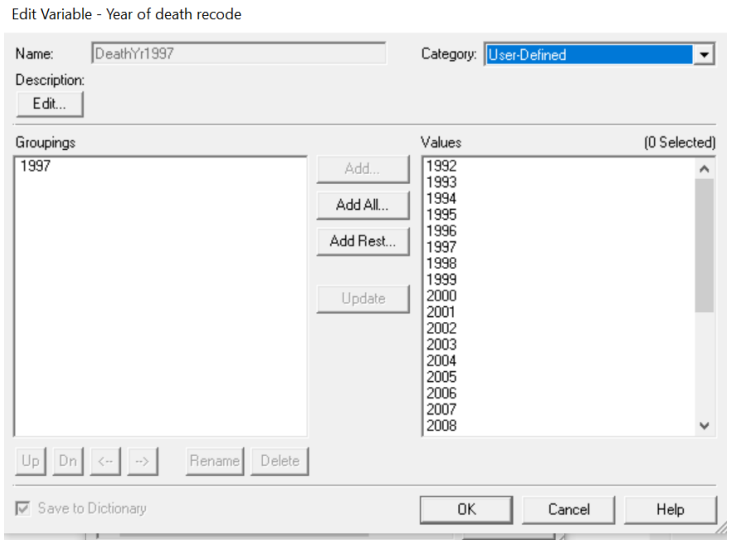
6. In the 'Table' section, add the specified death year into the column of the table, and add the lifetime variable into the row area of the table:



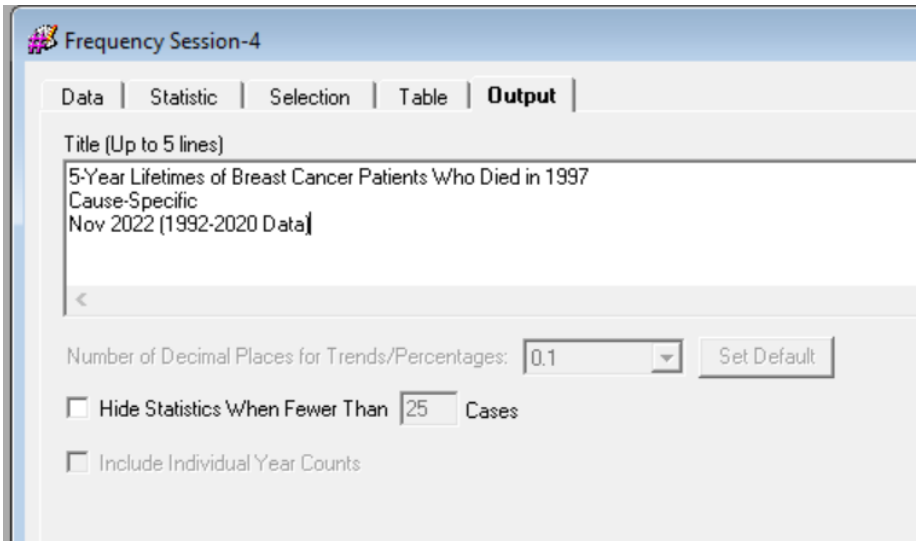
   a. An example of the custom merged Lifetime by 1997 year of death variable:



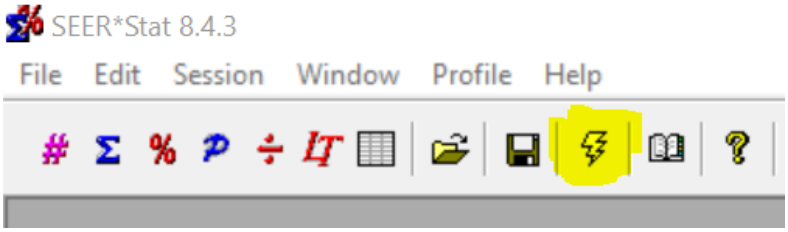
b. An example of the custom user-defined Death Year 1997 variable.



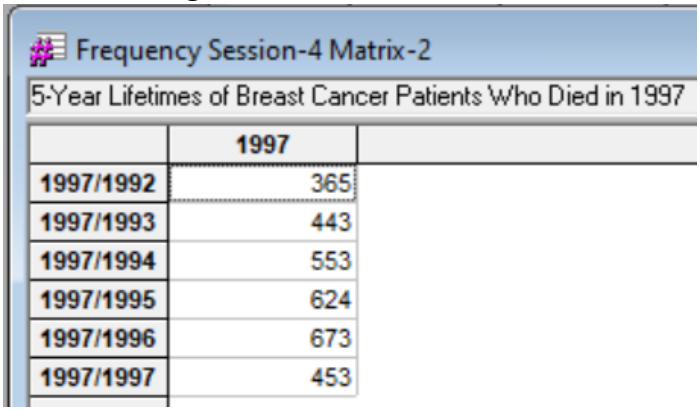
7. Under the ‘Output’ section, provide a meaningful title for the data set:



8. Execute the request:



9. Review findings:



	1997
1997/1992	365
1997/1993	443
1997/1994	553
1997/1995	624
1997/1996	673
1997/1997	453

Note: SEER provides the options to visualize the data in a graph format and export the results, as well as to save the query to edit in the future. Seer*Stat 9.0.30.0 in beta testing provides ever more enhanced visualizations than the previous version.

Curve Fitting

Logistic, linear, and exponential curves were all tested against 5-, 10- and 20-year cause-specific cancer survival data. Base code for each respective model may be found in the Appendix section. Findings were reviewed by comparing the sum of squared residuals (SSRs).

Predictions

For death year data, prediction curves were created by graphing predictions calculated using HTML files with embedded JavaScript code to analyze actual data extracted from SEER. Predictions for each death year incorporated variables derived from best fit curves based on 5-year, 10-year, and 20-year cancer survival data for cause-specific deaths.

Improved diagnosis year prediction curves were created by defining their key parameters by:

1. taking the trendline derived by Excel from diagnosis data extracted from SEER to determine a lifetime value at T0 (the y-intercept in the linear model, and the constant coefficient in the exponential model);
2. obtaining the steepness variable (doubling time in the exponential model, and slope in the linear model from a curve fitted to death year data extracted from SEER.

4. Results

4.1 Preliminary Findings

Preliminary findings were obtained for kidney and renal pelvis cancer.

Experiment 1

Historical survival trends for kidney and renal pelvis cancer were produced based on patient death year. Average cause-specific lifetimes were found to be increasing as of the year 2019:

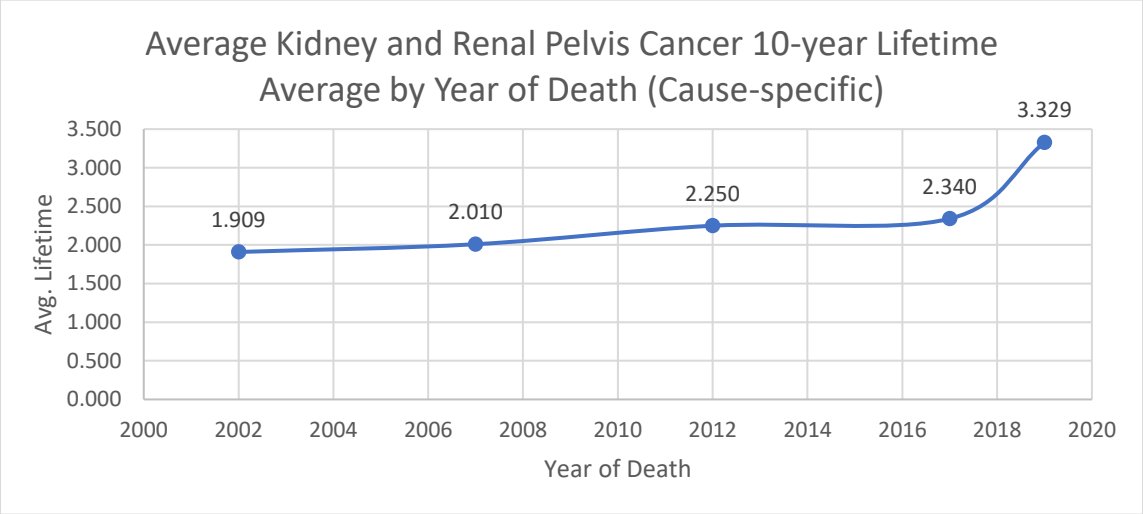


Figure 3: 10-year Average Kidney and Renal Pelvis Cancer Lifetimes by Year of Death

Experiment 2

Regression analysis was conducted on the dataset above. Using equation 6, we attempt to test for the appropriate values for ***C*** and ***D*** in equation 6 and compare the performance of each respective parameter for best fit by doing a sum of squares regression (SSR) against the data points in Figure 2. The best ***C*** value was found at 2.201 and the best ***D*** was found at 45 years. See Experiment 2 Output in appendix, for more information.

Experiment 3

Cause-specific survival times were also produced based on year of diagnosis in Figure 3. Note that in this figure, the independent variable is the SEER calculated survival metric calculated for historical data by diagnosis year, with a value of 1.000 meaning that the survival rate was 100% for a given diagnosis year:

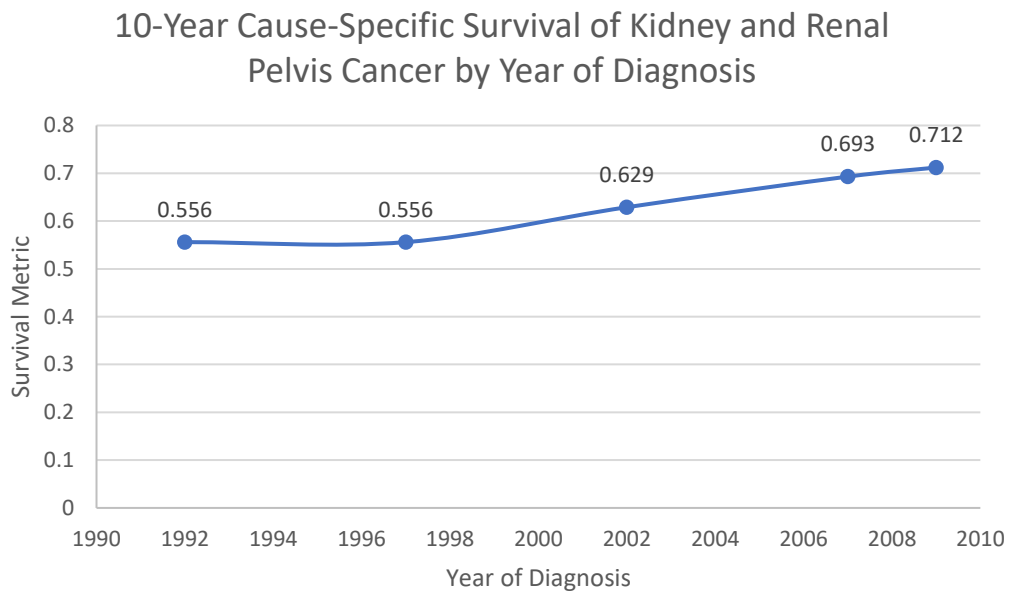


Figure 4: 10-Year Cause-specific Survival of Kidney and Renal Cancer by Year of Diagnosis

Experiment 4

We then use these best-calculated values for ***C*** *(2.201)* and ***D*** *(45)* and fit them into equation 3 for average lifetime predictions by diagnosis year:

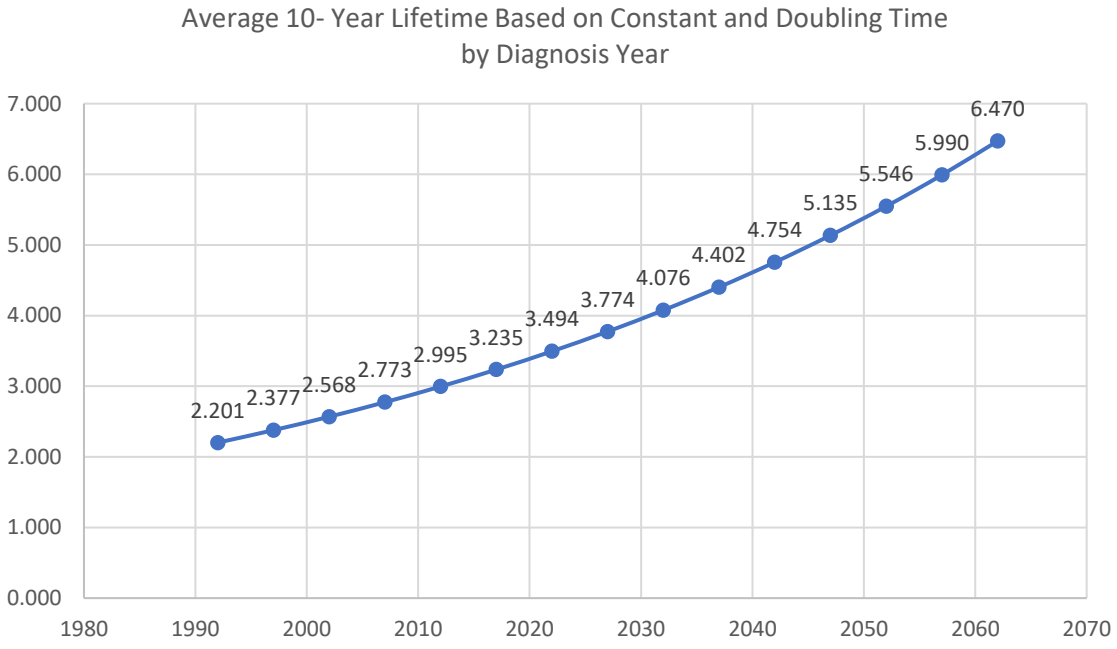


Figure 5: Average Kidney and Renal Pelvis Cancer Survival Time Using Ideal Parameters

Experiment 5

This allows us to determine a prediction model using equation (5) and year of death as the independent variable:

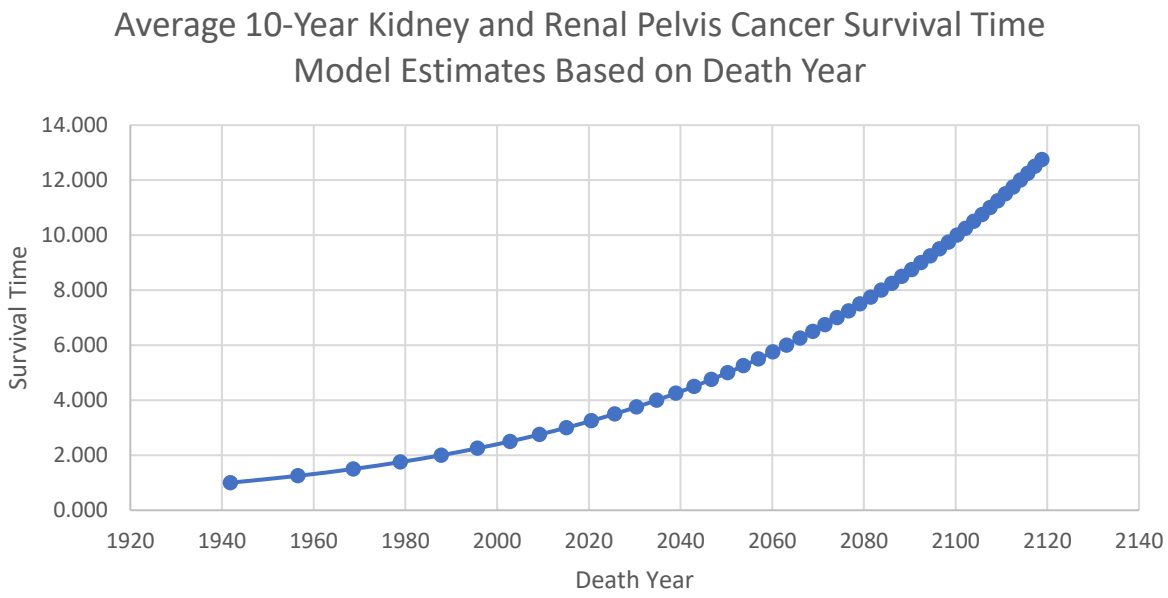


Figure 6: Average Kidney and Renal Cancer Survival Model by Year of Death

Using the findings above, we can easily plug in year of death to help us determine survival times.

4.2 Detailed Findings

4.2.1 Overall Trends

Below in Table 3, "trend" in this particular instance is defined as the difference between the beginning survival time and the most recent survival time given the timeframe. If the ending survival time is less than the beginning survival time, the trend is considered 'down'. If the ending survival time is greater than the beginning survival time, the trend is considered 'up'. Cells highlighted in Table 3 reflect instances where a year of death trend does not follow the same trend when comparing the same cancer type and time series by year of diagnosis. Note that this initial trend indication might or might not be corroborated by a deeper analysis of the data using curve fitting later.

By Year of Death					
Lifetime Horizon	Trend				
Years	Kidney	Myeloma	Lung	Prostate	Breast
5	Up	Up	Up	Down	Down
10	Up	Up	Up	Down	Down
20	Up	Up	Up	Down	Down

By Year of Diagnosis					
Lifetime Horizon	Trend				
Years	Kidney	Myeloma	Lung	Prostate	Breast
5	Up	Up	Up	Down	Down
10	Up	Up	Up	Down	Up
20	Up	Up	Up	Up	Up

Table 3: Overall, cause-specific initial survival trend estimates by cancer type, by year of death or diagnosis

4.2.2 Kidney and Renal Pelvis Cancer

Curve Fitting Findings

Cause-Specific Curve Models of Kidney & Renal Cancer Patients By Lifetime												
Lifetime Horizon	Exponential				Linear				Logistic			
	Doubling Time	Life at T_0 = 1990	Min. SSR	Mean Min. SSR per Year	Slope	Life at T_0	Min. SSR	Mean Min. SSR per Year	Midpoint	Steepness	Min. SSR	Mean Min. SSR per Year
5	70	1.090921	0.035631	0.001485	0.013150	1.070617	0.01603289	0.0006680	2086	0.013339	0.027979	0.0011658
10	43	1.576280	0.026003	0.001369	0.034891	1.486492	0.01173699	0.00061774	2074	0.019981	0.056484	0.0029728
20	35	2.252550	0.016400	0.001822	0.069082	1.966492	0.00765596	0.00085066	2076	0.024311	0.099427	0.0110474
MEAN (by model)				0.001558				0.000712				0.005062

Table 4: Comparison of cause-specific curve models for kidney and renal pelvis cancer Patients by lifetime horizon

4.2.3 Myeloma

Curve Fitting Findings

Cause-Specific Curve Models of Myeloma Patients By Survival Time												
Lifetime Horizon	Exponential				Linear				Logistic			
	Doubling Time	Life at T_0 = 1990	Min. SSR	Mean Min. SSR per Year	Slope	Life at T_0 = 1990	Min. SSR	Mean Min. SSR per Year	Midpoint	Steepness	Min. SSR	Mean Min. SSR per Year
5	247	1.68695	0.0292150	0.001217	0.004956	1.68588	0.013480	0.000562	2146	0.004327	0.042798	0.0017833
10	43	1.998081	0.0113574	0.000598	0.042410	1.916484	0.005798	0.000305	2054	0.021908	0.038255	0.0020134
20	25	1.942755	0.0078895	0.000877	0.102066	1.337411	0.003402	0.000378	2058	0.033121	0.051726	0.005747
Mean (by model)				0.000897				0.000415				0.0031813

Table 5: Comparison of cause-specific curve models for myeloma patients by lifetime horizon

4.2.4 Lung and Bronchus Cancer

Curve Fitting Findings

Cause-Specific Curve Models of Lung & Bronchus Cancer Patients By Lifetime												
Lifetime Horizon	Exponential				Linear				Logistic			
	Doubling Time	Life at T_0	Min. SSR	Mean Min SSR per year	Slope	Life at T_0	Min. SSR	Mean Min SSR per year	Midpoint	Steepness	Min. SSR	Mean Min SSR per year
5	58	0.741584	0.013134	0.000547	0.010819	0.727833	0.00748	0.00031	2108	0.014889	0.006110	0.000255
10	38	0.833067	0.013044	0.000687	0.021420	0.776672	0.00783	0.00041	2103	0.021415	0.010578	0.000557
20	26	0.812333	0.003765	0.000418	0.040391	0.574211	0.00216	0.00024	2098	0.029569	0.004687	0.000521
MEAN (by model)				0.000551				0.00032				0.000148

Table 6: Comparison of cause-specific curve models for lung and bronchus cancer patients by lifetime horizon

4.2.5 Prostate Cancer

Curve Fitting Findings

Cause-Specific Curve Models of Prostate Cancer Patients By Lifetime												
Lifetime Horizon	Exponential				Linear				Logistic			
	Doubling Time	Life at T_0	Min. SSR	Mean Min SSR per year	Slope	Life at T_0	Min. SSR	Mean Min SSR per year	Midpoint	Steepness	Min. SSR	Mean Min SSR per year
5	Future Work	Future Work	Future Work	Future Work	0.000100	2.182541	0.109316	0.004555	4362	0.000105	0.592694	0.024696
10	Future Work	Future Work	Future Work	Future Work	0.000100	4.05906	0.085267	0.004488	8800	0.000055	1.542348	0.081176
20	Future Work	Future Work	Future Work	Future Work	0.000100	7.13288	0.013078	0.001453	4622	0.000416	0.295504	0.032834
MEAN (by model)								0.003499				0.046235

Table 7: Comparison of cause-specific Curve models for prostate cancer patients by lifetime horizon

The following tables give a more detailed, alternative analysis of the prostate cancer domain. In this different analysis, average survival time is calculated using the percentages of patients surviving each post-diagnosis year, instead of the percentages dying each post-diagnosis year.

Prostate Cancer Death Counts by Year of Diagnosis							
Dx. Year	# Dx'd	Dx Year + 0	Dx Year + 1	Dx Year + 2	Dx Year + 3	Dx Year + 4	Dx Year + 5
1992	25,512	332	538	592	447	443	380
1993	23,029	340	493	493	432	348	323
1994	20,454	321	431	392	367	281	290
1995	19,680	297	442	403	306	282	219
1996	20,053	299	396	390	303	257	236
1997	21,100	291	356	358	288	240	266
1998	21,046	307	387	309	254	260	230
1999	22,964	302	371	320	291	267	228
2000	23,219	308	358	351	305	228	245
2001	23,926	312	323	295	263	238	193
2002	24,155	325	364	278	283	200	200
2003	23,192	282	345	316	231	234	217
2004	23,867	267	365	279	244	216	174
2005	23,098	347	337	323	251	216	190
2006	25,199	342	353	326	256	216	181
2007	26,424	341	321	270	235	226	204
2008	25,136	287	325	317	255	192	193
2009	25,496	321	392	277	258	206	172
2010	25,012	290	359	271	238	214	172
2011	24,643	301	370	292	239	192	195
2012	21,013	304	355	268	212	194	180
2013	20,848	332	400	308	301	201	179
2014	19,680	387	369	347	244	228	177
2015	21,061	379	446	336	338	233	203

Table 8: Prostate Cancer Death Counts from Diagnosis Years 1992-2015

Prostate Cancer Death Percentages by Year of Diagnosis							
Dx. Year	# Dx'd	Dx Year + 0 %	Dx Year + 1 %	Dx Year + 2 %	Dx Year + 3 %	Dx Year + 4 %	Dx Year + 5 %
1992	25,512	1.30%	2.11%	2.32%	1.75%	1.74%	1.49%
1993	23,029	1.48%	2.14%	2.14%	1.88%	1.51%	1.40%
1994	20,454	1.57%	2.11%	1.92%	1.79%	1.37%	1.42%
1995	19,680	1.51%	2.25%	2.05%	1.55%	1.43%	1.11%
1996	20,053	1.49%	1.97%	1.94%	1.51%	1.28%	1.18%
1997	21,100	1.38%	1.69%	1.70%	1.36%	1.14%	1.26%
1998	21,046	1.46%	1.84%	1.47%	1.21%	1.24%	1.09%
1999	22,964	1.32%	1.62%	1.39%	1.27%	1.16%	0.99%
2000	23,219	1.33%	1.54%	1.51%	1.31%	0.98%	1.06%
2001	23,926	1.30%	1.35%	1.23%	1.10%	0.99%	0.81%
2002	24,155	1.35%	1.51%	1.15%	1.17%	0.83%	0.83%
2003	23,192	1.22%	1.49%	1.36%	1.00%	1.01%	0.94%
2004	23,867	1.12%	1.53%	1.17%	1.02%	0.91%	0.73%
2005	23,098	1.50%	1.46%	1.40%	1.09%	0.94%	0.82%
2006	25,199	1.36%	1.40%	1.29%	1.02%	0.86%	0.72%
2007	26,424	1.29%	1.21%	1.02%	0.89%	0.86%	0.77%
2008	25,136	1.14%	1.29%	1.26%	1.01%	0.76%	0.77%
2009	25,496	1.26%	1.54%	1.09%	1.01%	0.81%	0.67%
2010	25,012	1.16%	1.44%	1.08%	0.95%	0.86%	0.69%
2011	24,643	1.22%	1.50%	1.18%	0.97%	0.78%	0.79%
2012	21,013	1.45%	1.69%	1.28%	1.01%	0.92%	0.86%
2013	20,848	1.59%	1.92%	1.48%	1.44%	0.96%	0.86%
2014	19,680	1.97%	1.88%	1.76%	1.24%	1.16%	0.90%
2015	21,061	1.80%	2.12%	1.60%	1.60%	1.11%	0.96%

Table 9: Prostate Cancer Death Percentages from Diagnosis Years 1992-2015

Prostate Cancer Survival : Years Lost Per Patient (Avg.)								
Dx. Year	# Dx'd	Dx+0 surv%	Dx+1 surv%	Dx+2 surv%	Dx+3 surv%	Dx+4 surv%	Dx+5 surv%	Patient Years Lost by End of Year 5
1992	25,512	98.70%	96.59%	94.27%	92.52%	90.78%	89.29%	0.3250
1993	23,029	98.52%	96.38%	94.24%	92.37%	90.86%	89.45%	0.3290
1994	20,454	98.43%	96.32%	94.41%	92.61%	91.24%	89.82%	0.3208
1995	19,680	98.49%	96.24%	94.20%	92.64%	91.21%	90.10%	0.3217
1996	20,053	98.51%	96.53%	94.59%	93.08%	91.80%	90.62%	0.3018
1997	21,100	98.62%	96.93%	95.24%	93.87%	92.73%	91.47%	0.2686
1998	21,046	98.54%	96.70%	95.23%	94.03%	92.79%	91.70%	0.2685
1999	22,964	98.68%	97.07%	95.68%	94.41%	93.25%	92.25%	0.2479
2000	23,219	98.67%	97.13%	95.62%	94.31%	93.32%	92.27%	0.2481
2001	23,926	98.70%	97.35%	96.11%	95.01%	94.02%	93.21%	0.2221
2002	24,155	98.65%	97.15%	96.00%	94.83%	94.00%	93.17%	0.2279
2003	23,192	98.78%	97.30%	95.93%	94.94%	93.93%	92.99%	0.2262
2004	23,867	98.88%	97.35%	96.18%	95.16%	94.26%	93.53%	0.2140
2005	23,098	98.50%	97.04%	95.64%	94.55%	93.62%	92.80%	0.2425
2006	25,199	98.64%	97.24%	95.95%	94.93%	94.08%	93.36%	0.2248
2007	26,424	98.71%	97.49%	96.47%	95.58%	94.73%	93.96%	0.2003
2008	25,136	98.86%	97.57%	96.30%	95.29%	94.53%	93.76%	0.2058
2009	25,496	98.74%	97.20%	96.12%	95.11%	94.30%	93.62%	0.2172
2010	25,012	98.84%	97.41%	96.32%	95.37%	94.51%	93.83%	0.2063
2011	24,643	98.78%	97.28%	96.09%	95.12%	94.34%	93.55%	0.2161
2012	21,013	98.55%	96.86%	95.59%	94.58%	93.66%	92.80%	0.2436
2013	20,848	98.41%	96.49%	95.01%	93.57%	92.60%	91.75%	0.2805
2014	19,680	98.03%	96.16%	94.40%	93.16%	92.00%	91.10%	0.3071
2015	21,061	98.20%	96.08%	94.49%	92.88%	91.78%	90.81%	0.3116

Table 10: Prostate Cancer Average Years Lost Per Patient Years 1992-2015

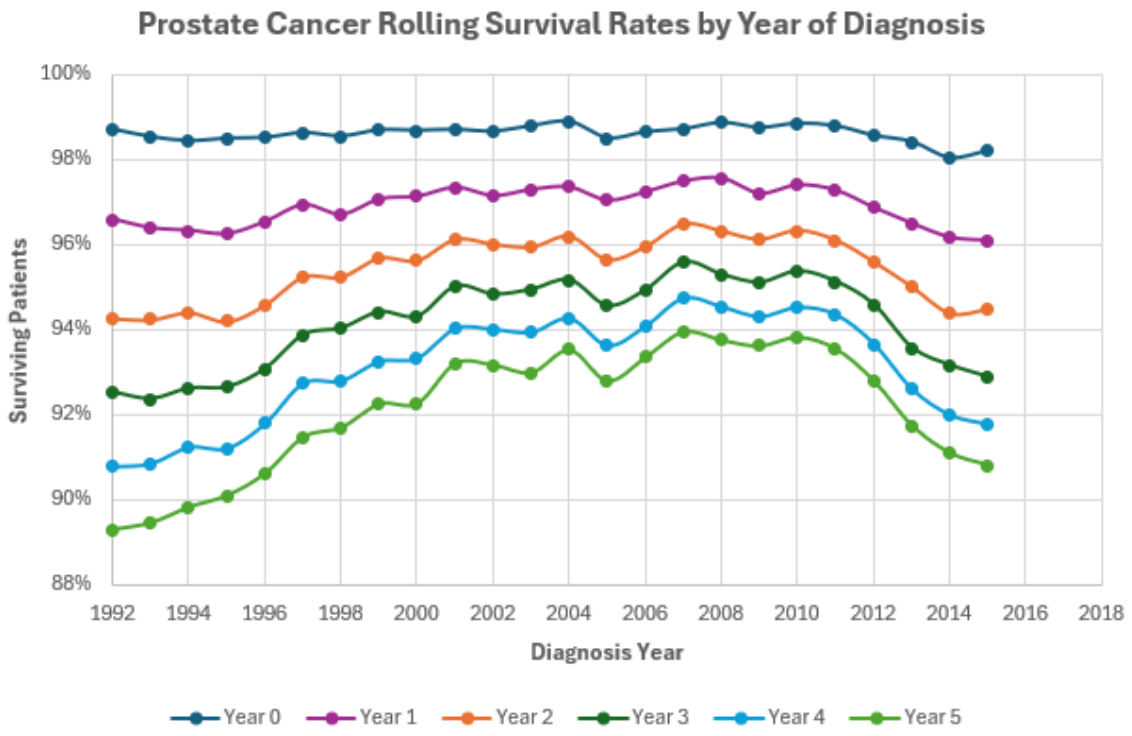


Figure 7: Prostate cancer rolling survival rate trend from diagnosis Years 1992-2015 (Diagnosis Year + 5 years horizon)

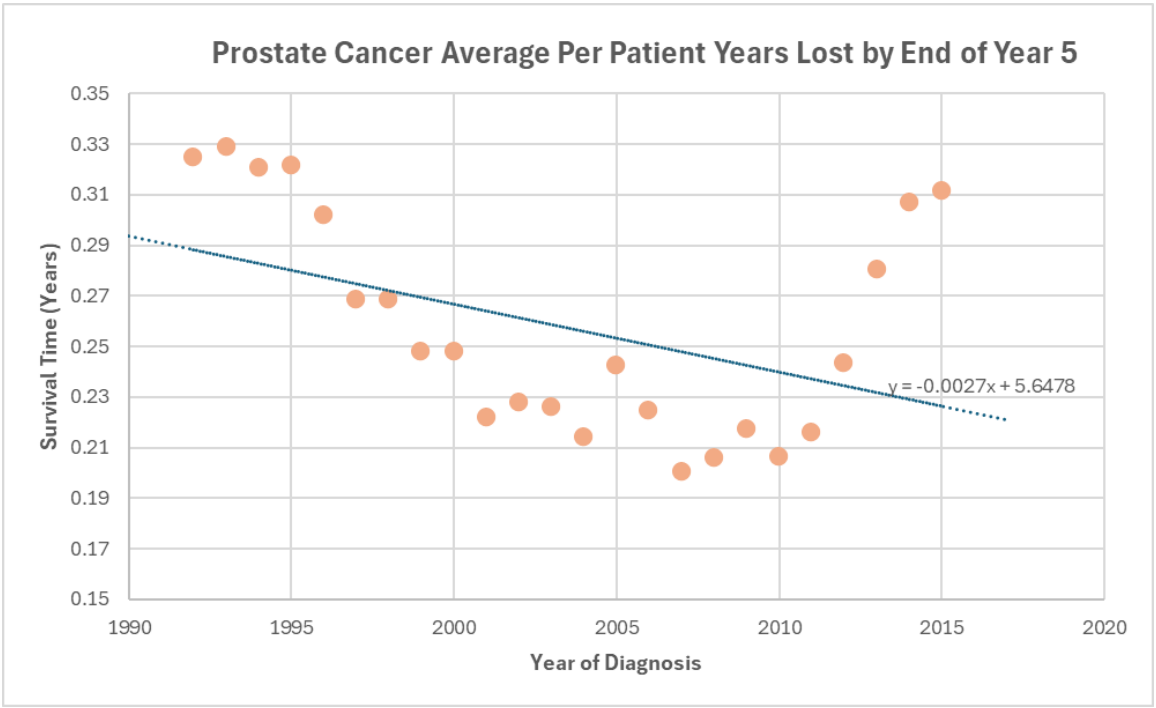


Figure 8: Prostate cancer average per patient-years lost by the end of Year 5 for diagnosis Years 1992-2015

4.2.6 Breast Cancer

Curve Fitting Findings

Cause-Specific Curve Models of Breast Cancer Patients By Lifetime												
Lifetime Horizon	Exponential				Linear				Logistic			
	Doubling Time	Life at T_0 =1990	Min. SSR	Mean Min SSR per year	Slope	Life at T_0 = 1990	Min. SSR	Mean Min SSR per year	Midpoint	Steepness	Min. SSR	Mean Min SSR per year
5	Future Work	Future Work	Future Work	Future Work	0.000100	2.317437	0.010020	0.000418	3811	0.000080	0.055316	0.002305
10	Future Work	Future Work	Future Work	Future Work	0.000100	3.828070	0.013957	0.000735	6480	0.000106	0.216551	0.011397
20	Future Work	Future Work	Future Work	Future Work	0.000100	5.945966	0.002831	0.000315	3358	0.000637	0.109699	0.012189
MEAN (by model)								0.0004889				0.008630

Table 11: Comparison of cause-specific curve models for breast cancer patients by lifetime horizon

4.3 Future Predictions

4.3.1 Kidney and Renal Pelvis Cancer

5-Year Survival Time Predictions

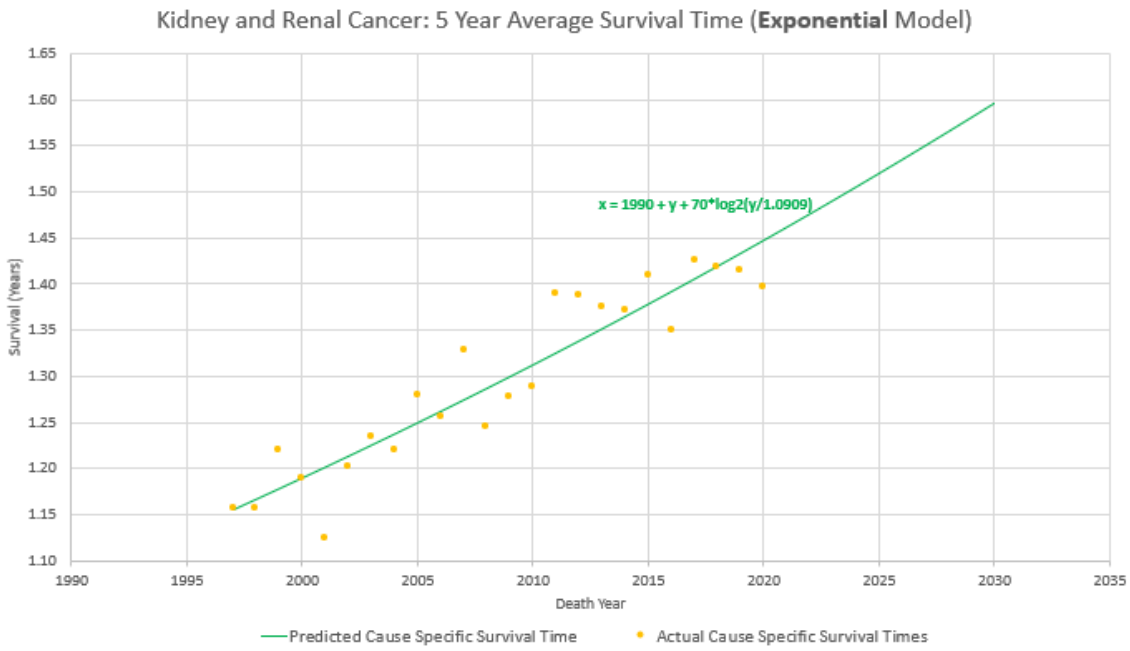


Figure 9: 5-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Exponential Model Predictions by Year of Death

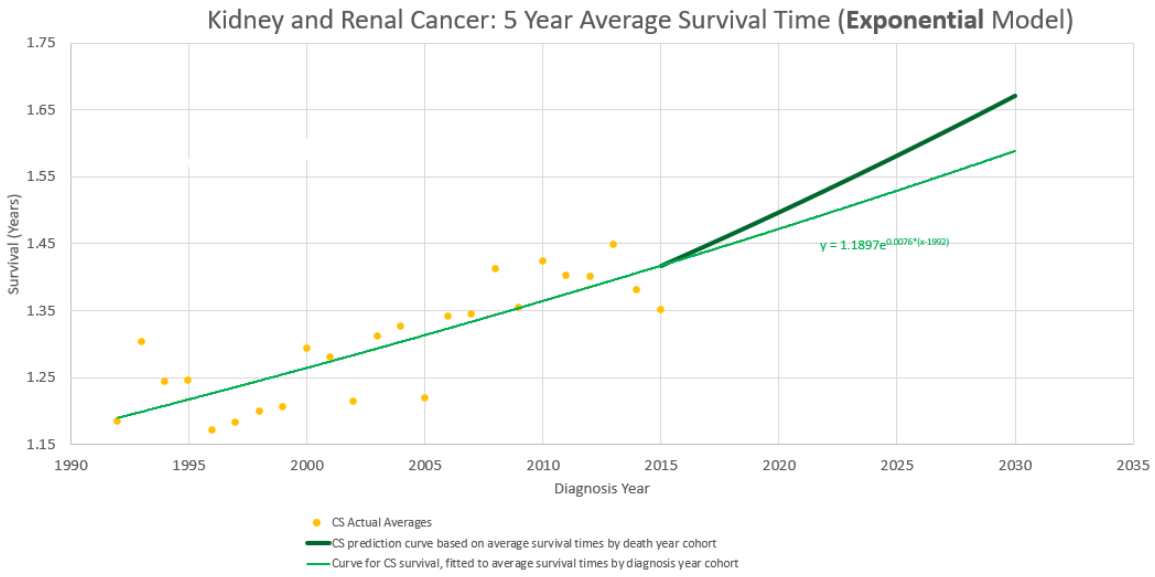


Figure 10: 5-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

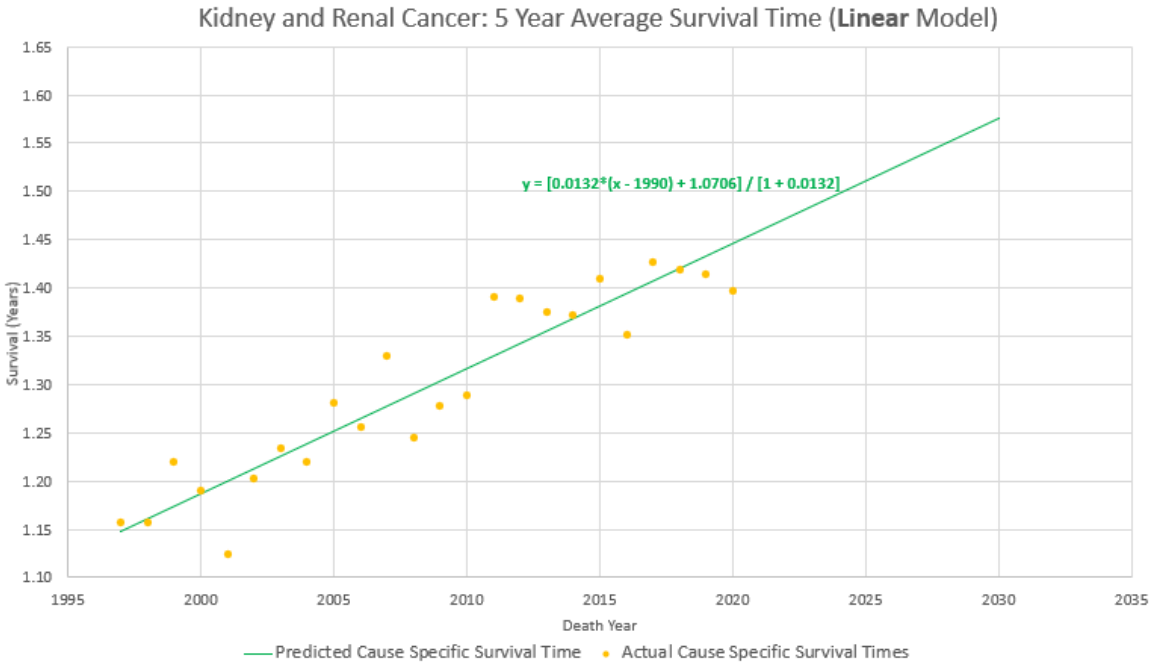


Figure 11: 5-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Linear Model Predictions by Year of Death

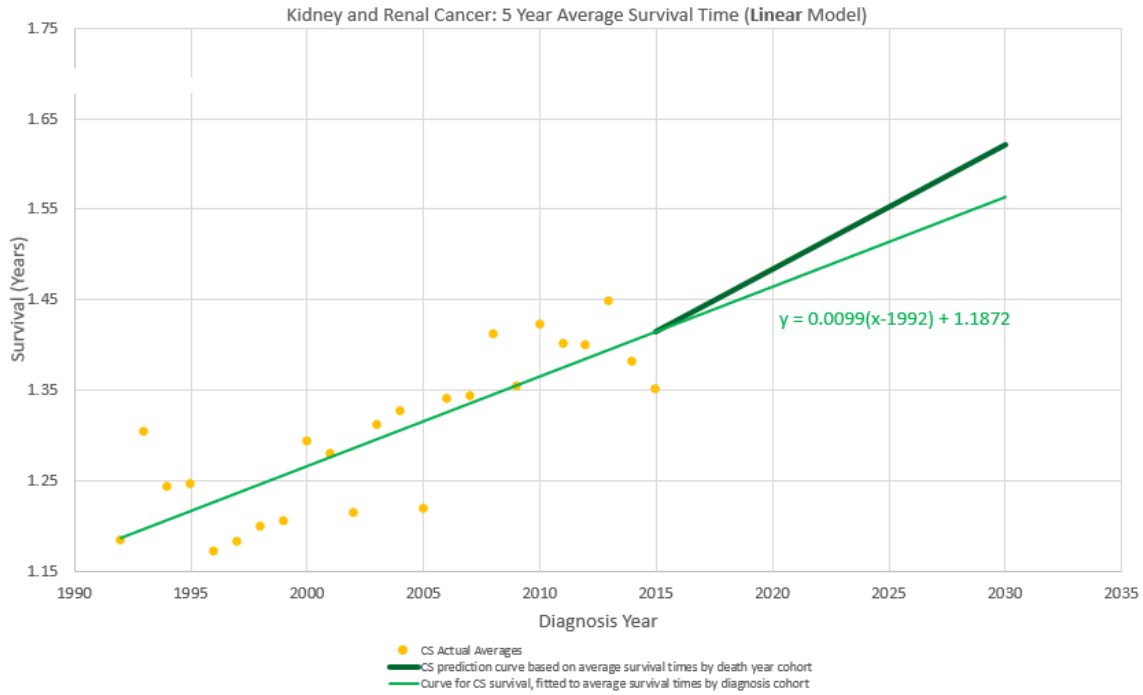


Figure 12: 5-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Linear Model Predictions by Year of Diagnosis

10-Year Survival Time Predictions

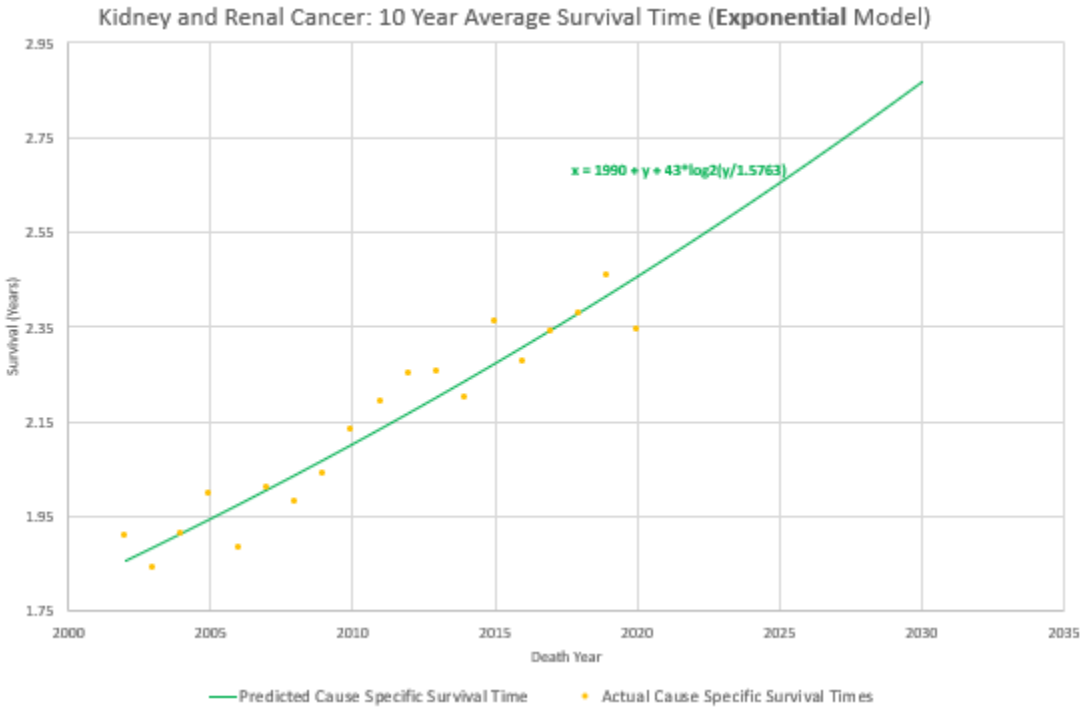


Figure 13: 10-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Exponential Model Predictions by Year of Death

Figure 14: 10-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

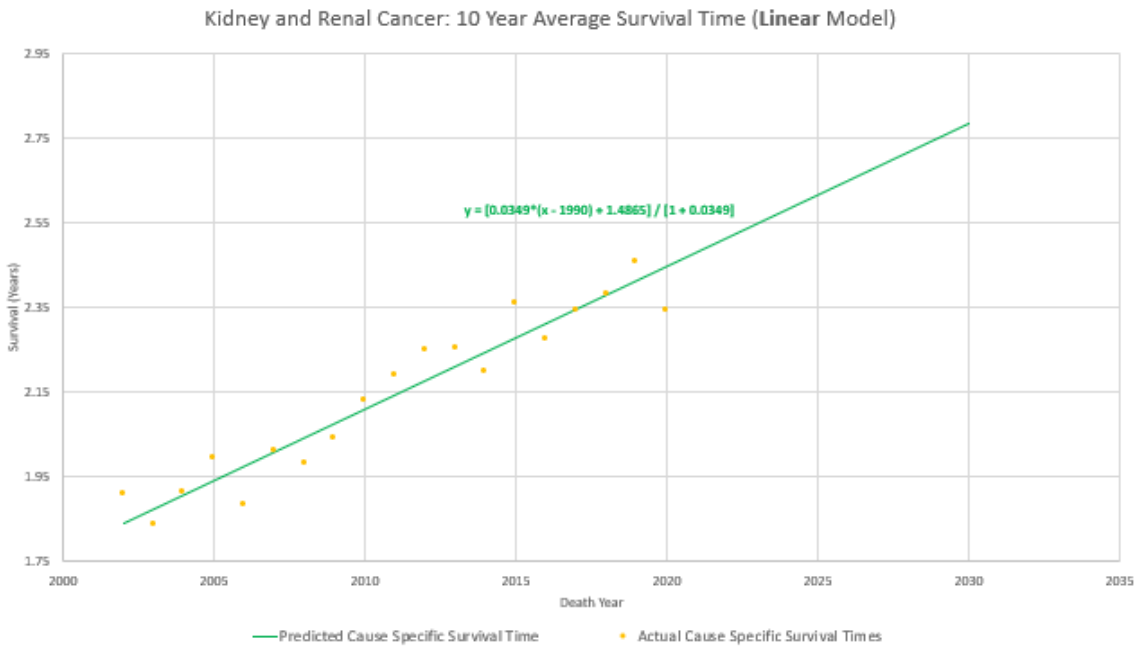


Figure 15: 10-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Linear Model Predictions by Year of Death

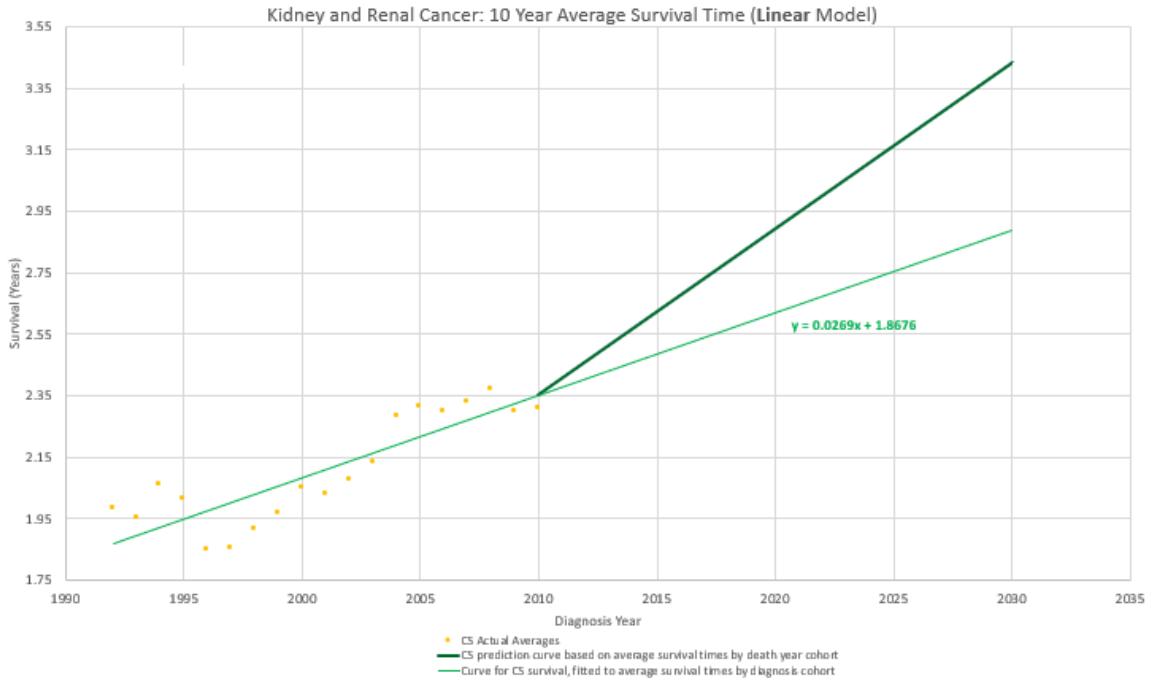


Figure 16: 10-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Linear Model Predictions by Year of Diagnosis

20-Year Survival Time Predictions

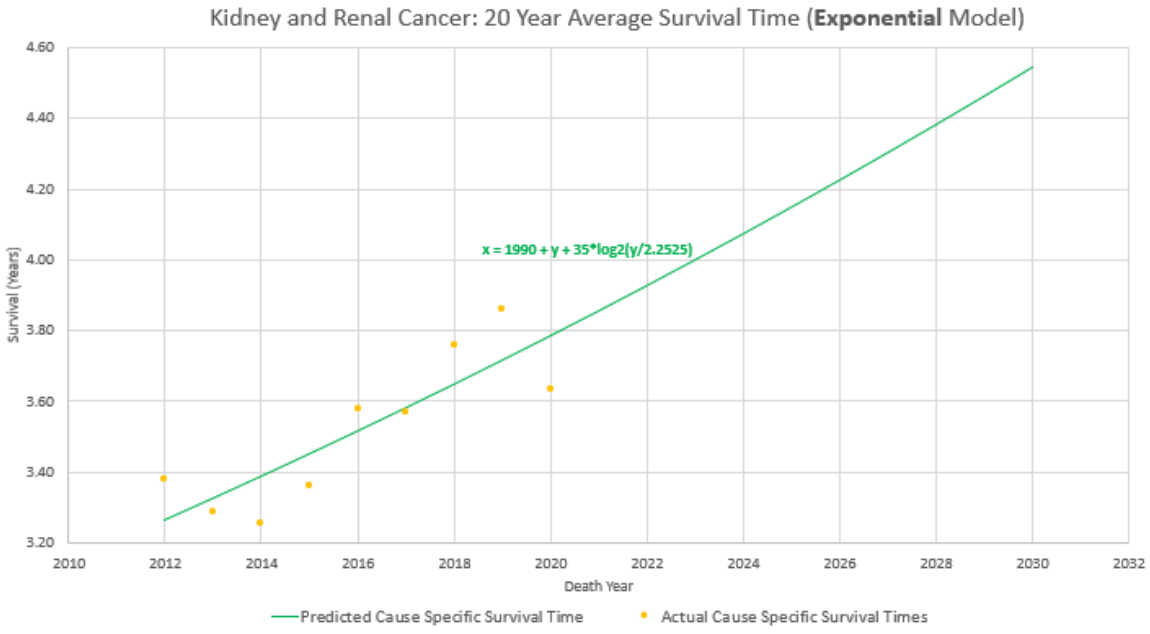


Figure 17: 20-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Exponential Model Predictions by Year of Death

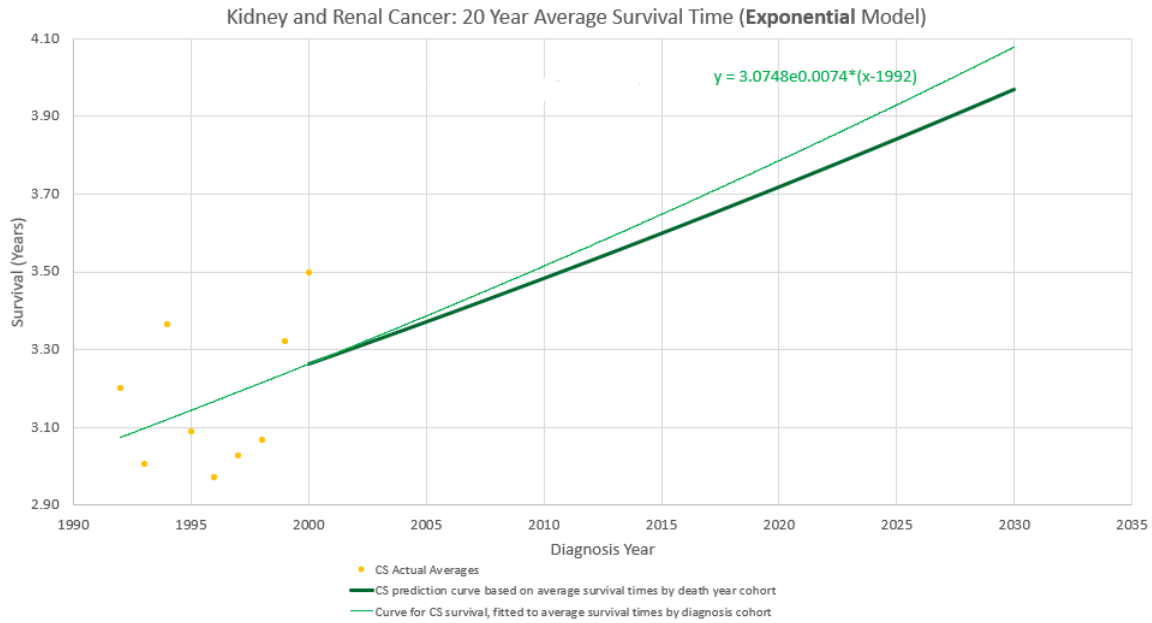


Figure 18: 20-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

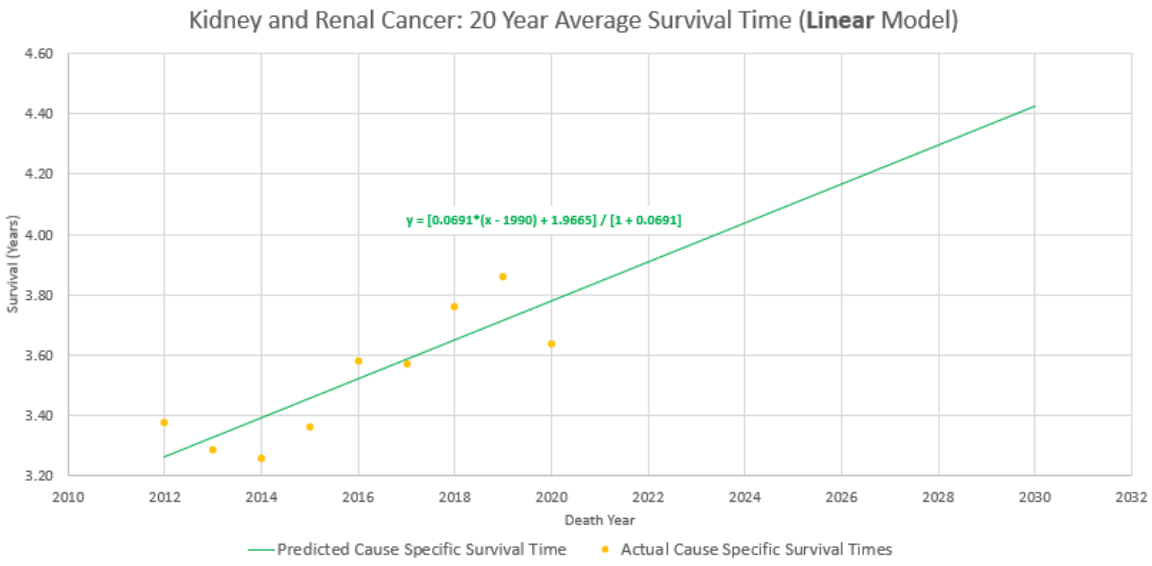


Figure 19: 20-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Linear Model Predictions by Year of Death

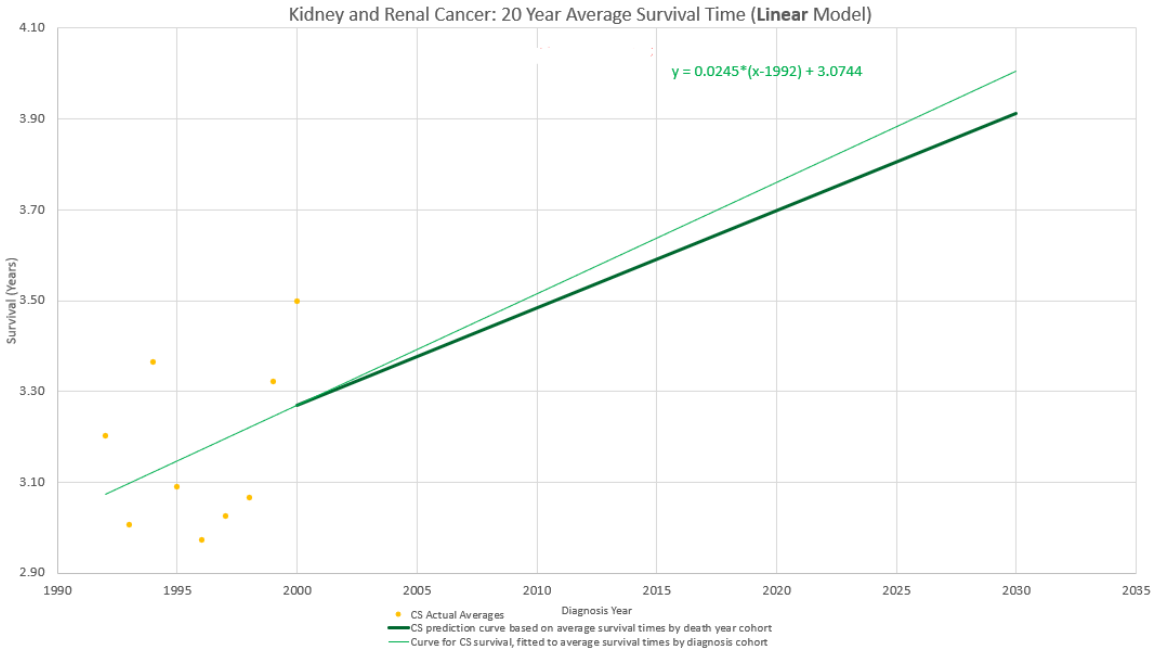


Figure 20: 20-Year Cause-specific Kidney and Renal Cancer Avg. Survival Time Linear Model Predictions by Year of Diagnosis

4.3.2 Myeloma

5-Year Survival Time Predictions

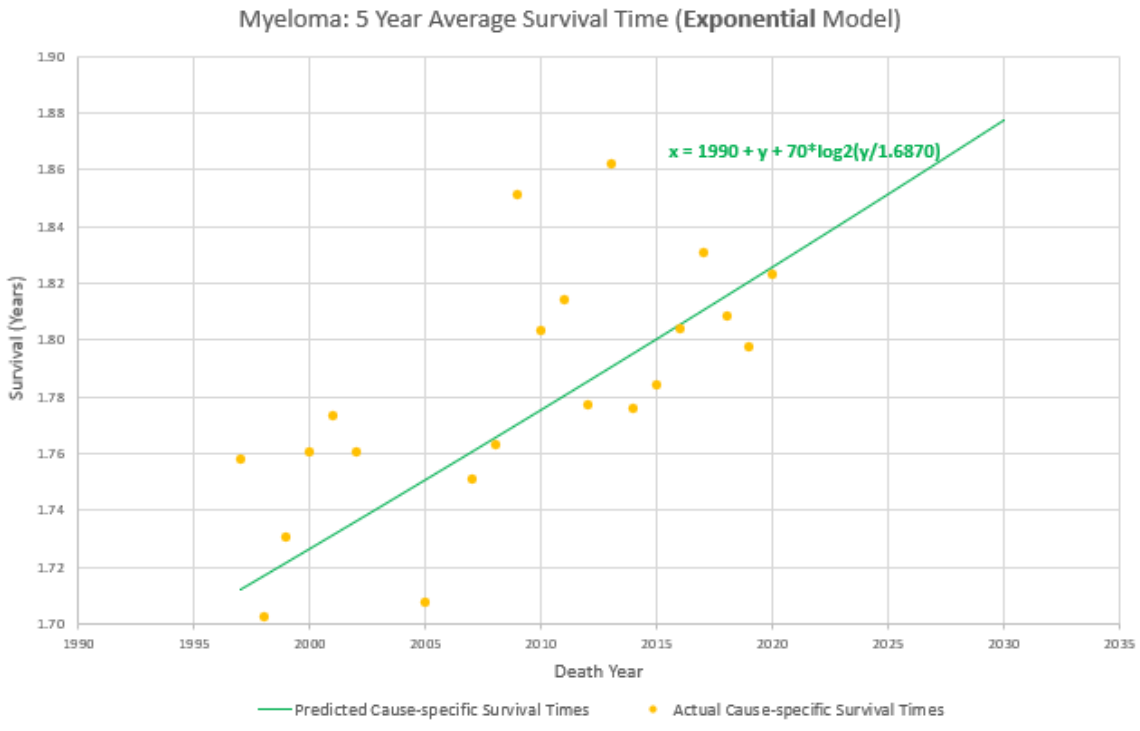


Figure 21: 5-Year Cause-specific Myeloma Avg. Survival Time Exponential Model Predictions by Year of Death

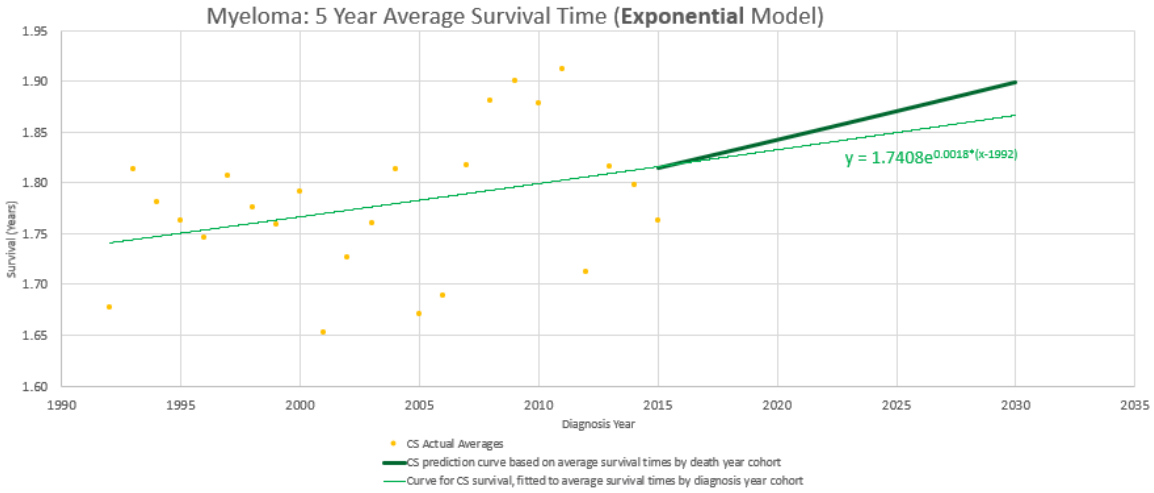


Figure 22: 5-Year Cause-specific Myeloma Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

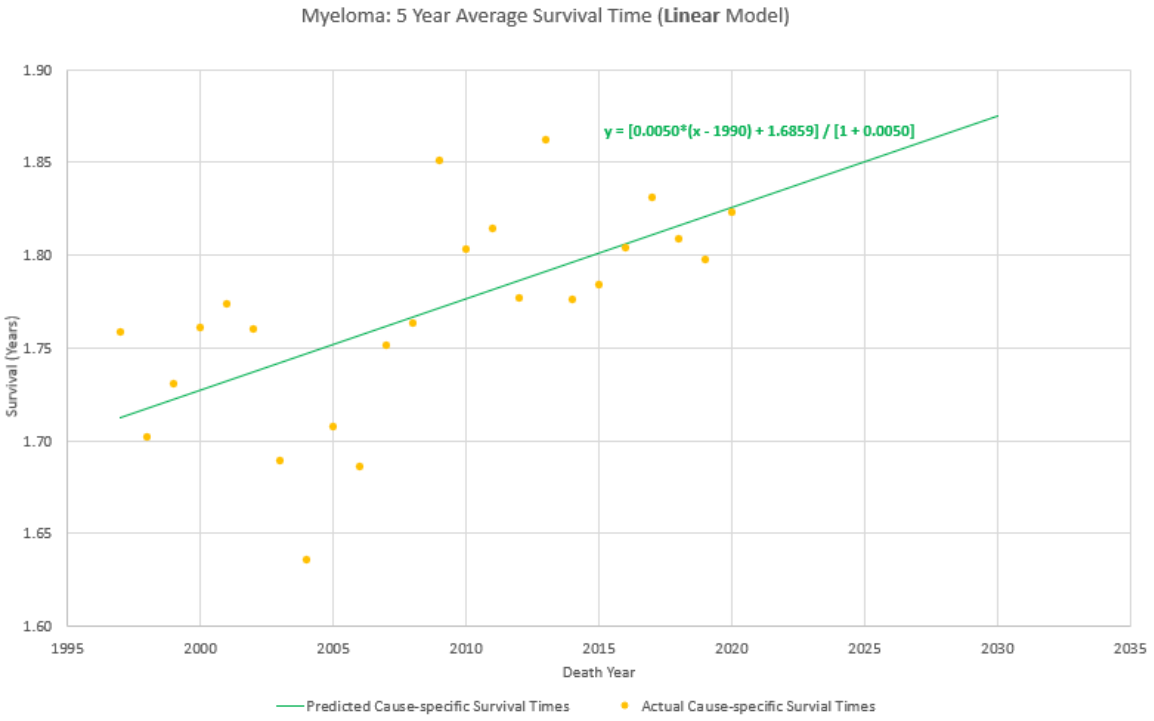


Figure 23: 5-Year Cause-specific Myeloma Avg. Survival Time Linear Model Predictions by Year of Death

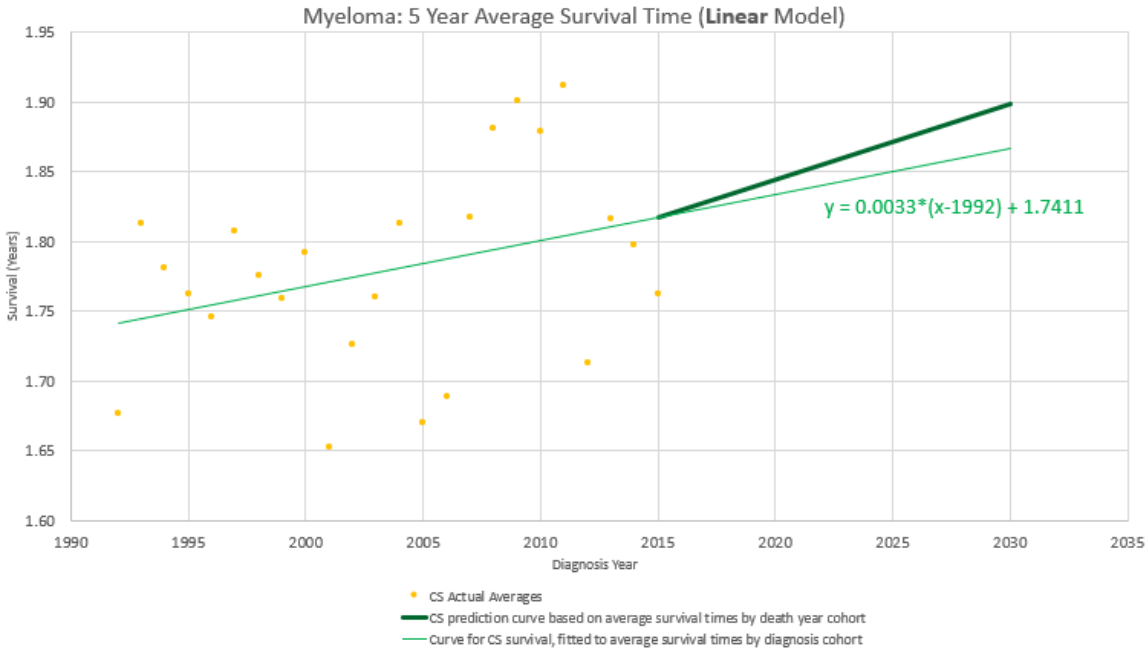


Figure 24: 5-Year Cause-specific Myeloma Avg. Survival Time Linear Model Predictions by Year of Diagnosis

10-Year Survival Time Predictions

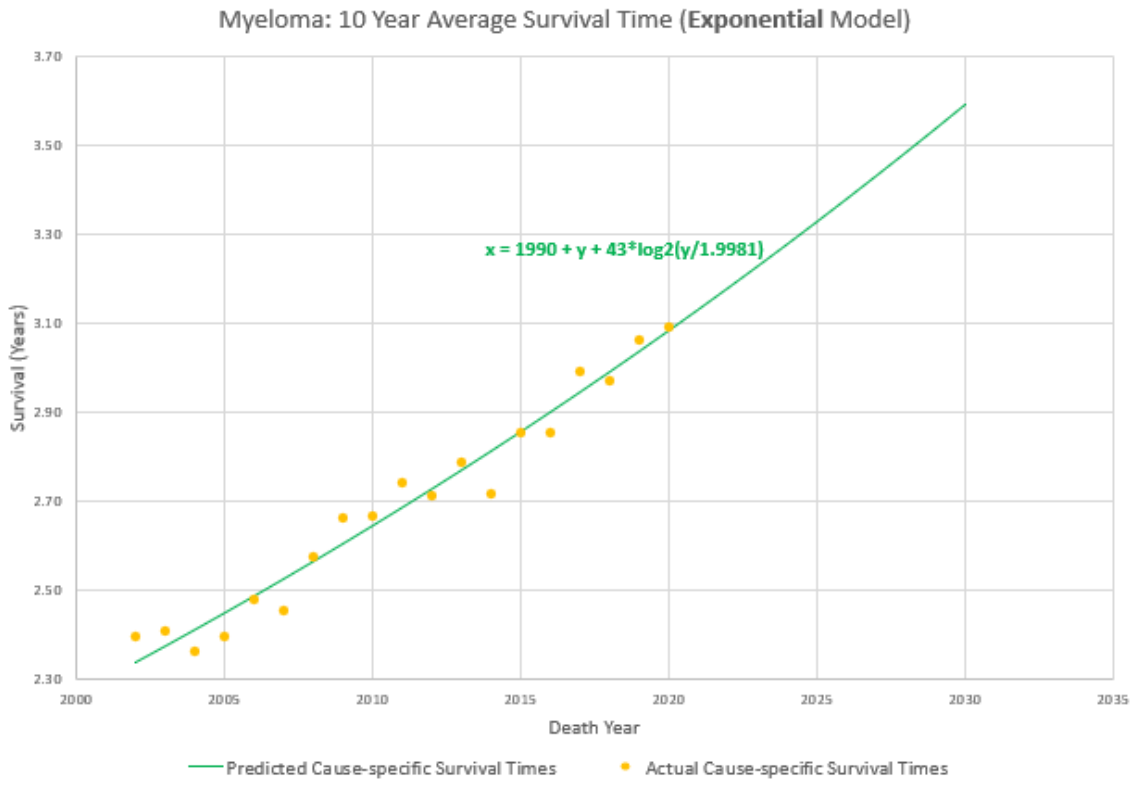


Figure 25: 10-Year Cause-specific Myeloma Avg. Survival Time Exponential Model Predictions by Year of Death

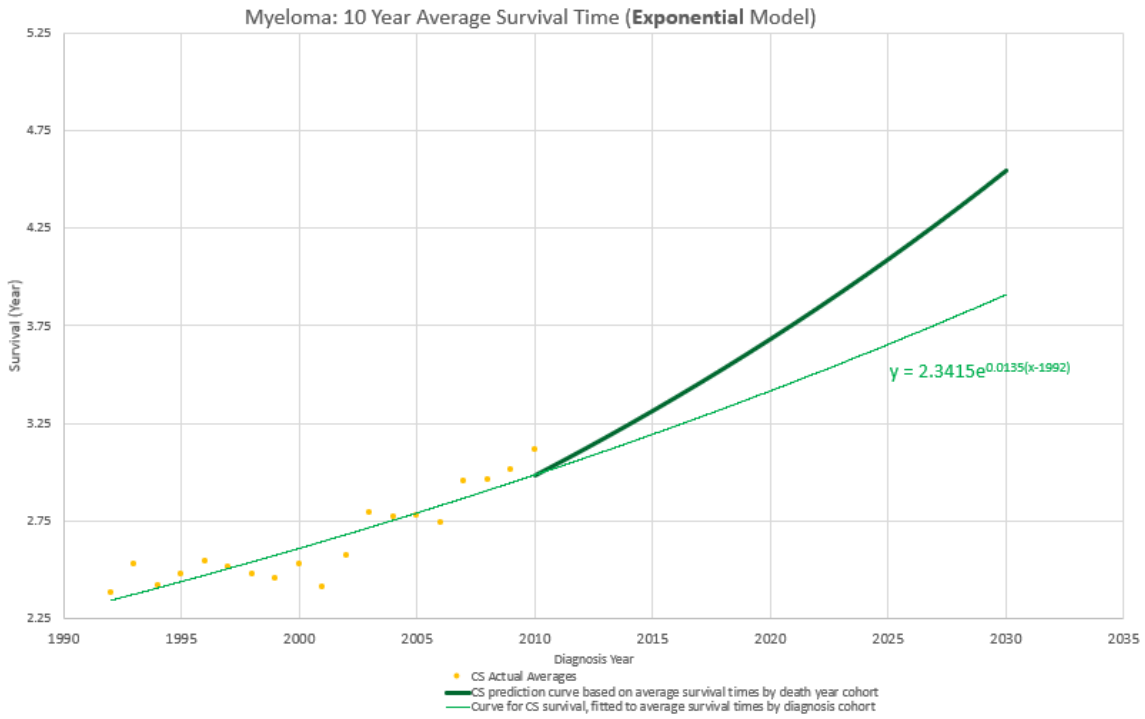


Figure 26: 10-Year Cause-specific Myeloma Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

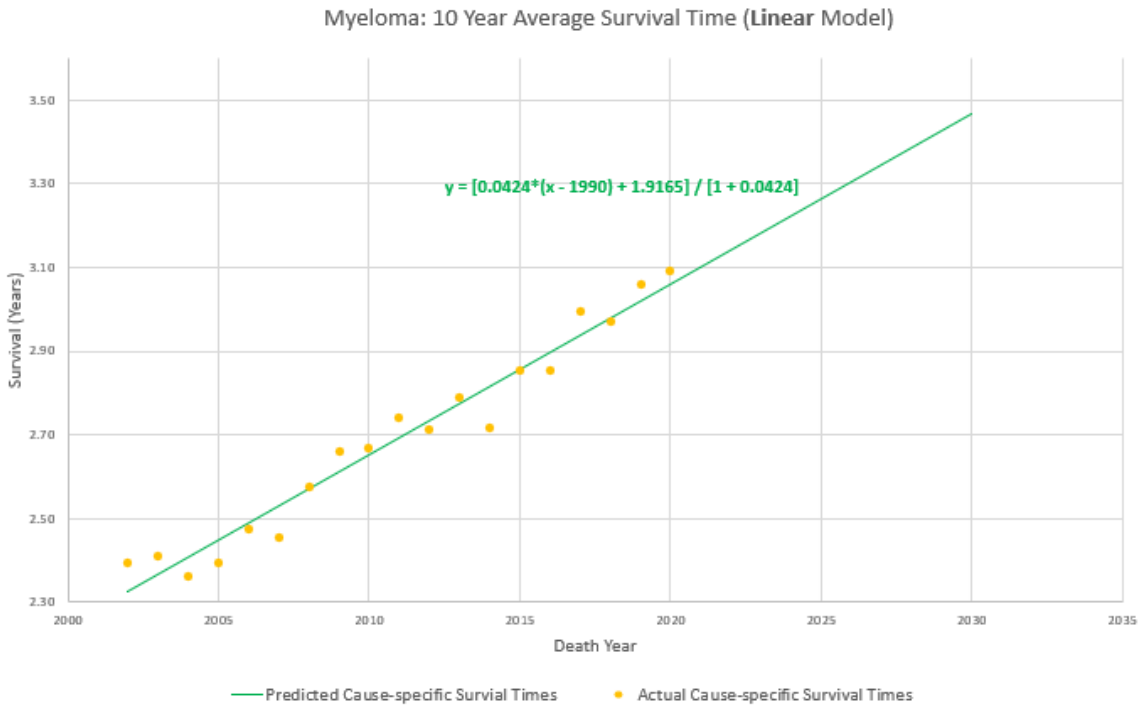


Figure 27: 10-Year Cause-specific Myeloma Avg. Survival Time Linear Model Predictions by Year of Death

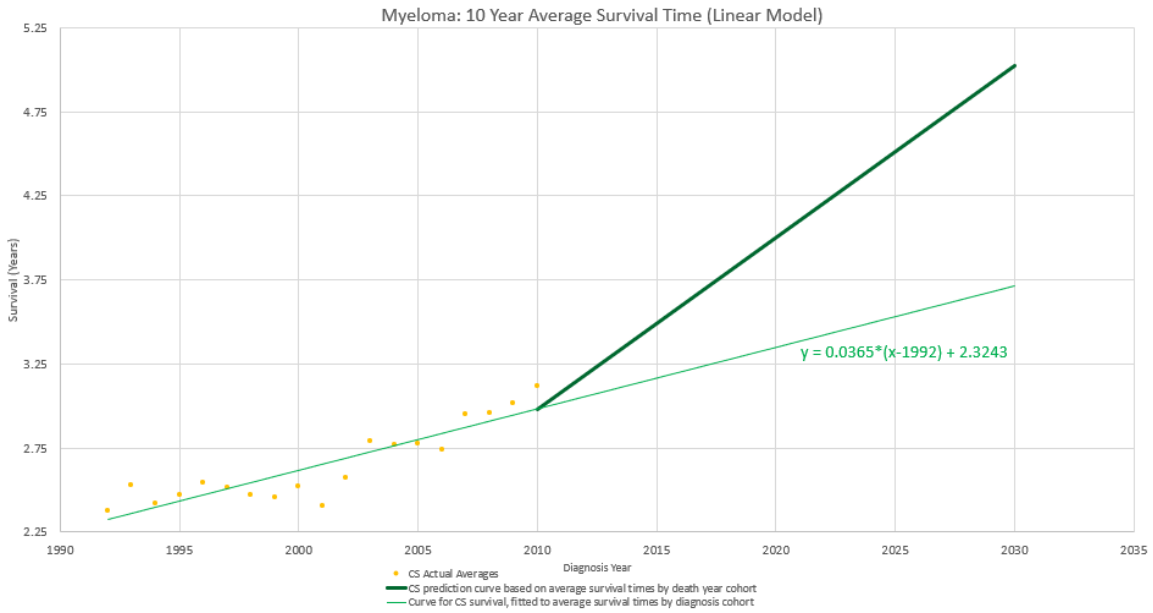


Figure 28: 10-Year Cause-specific Myeloma Avg. Survival Time Linear Model Predictions by Year of Diagnosis

20-Year Survival Time Predictions

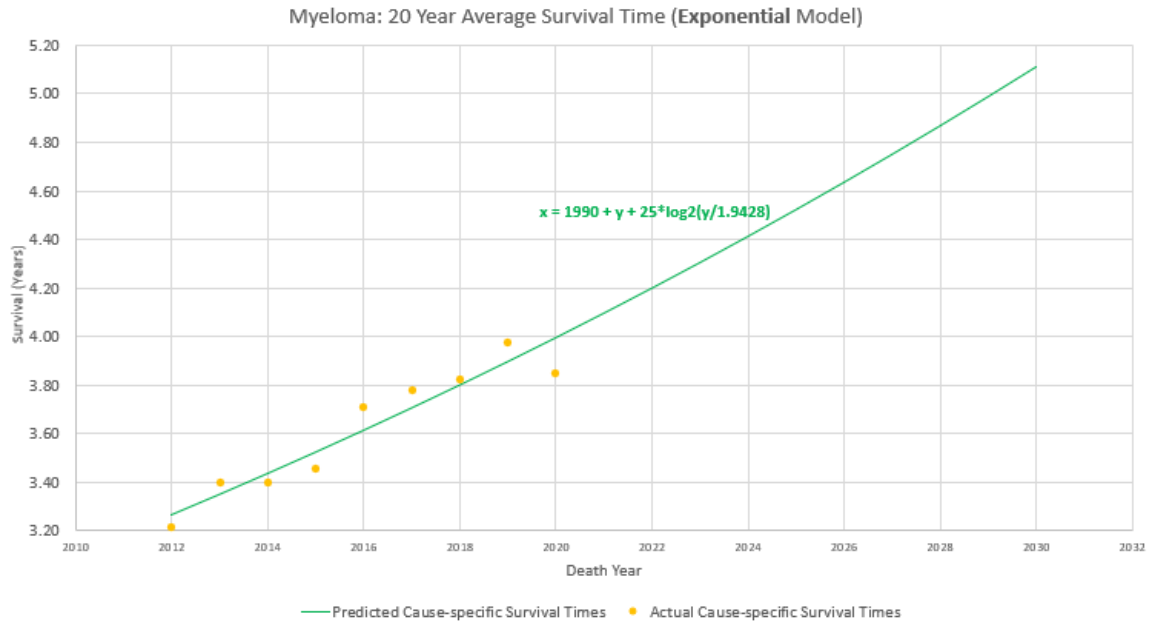


Figure 29: 20-Year Cause-specific Myeloma Avg. Survival Time Exponential Model Predictions by Year of Death

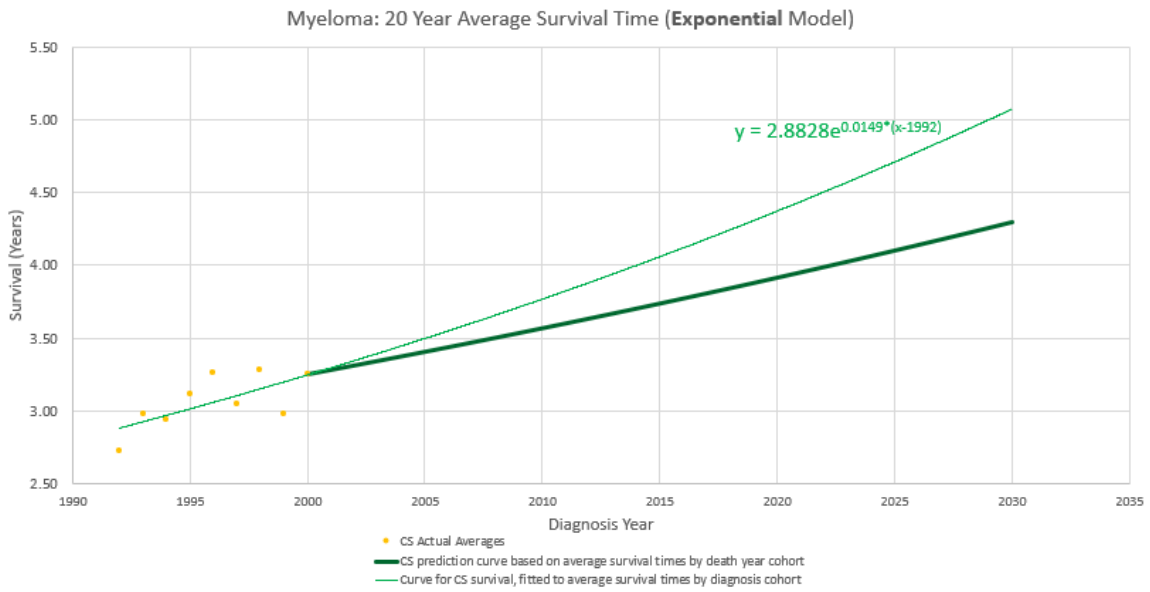


Figure 30: 20-Year Cause-specific Myeloma Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

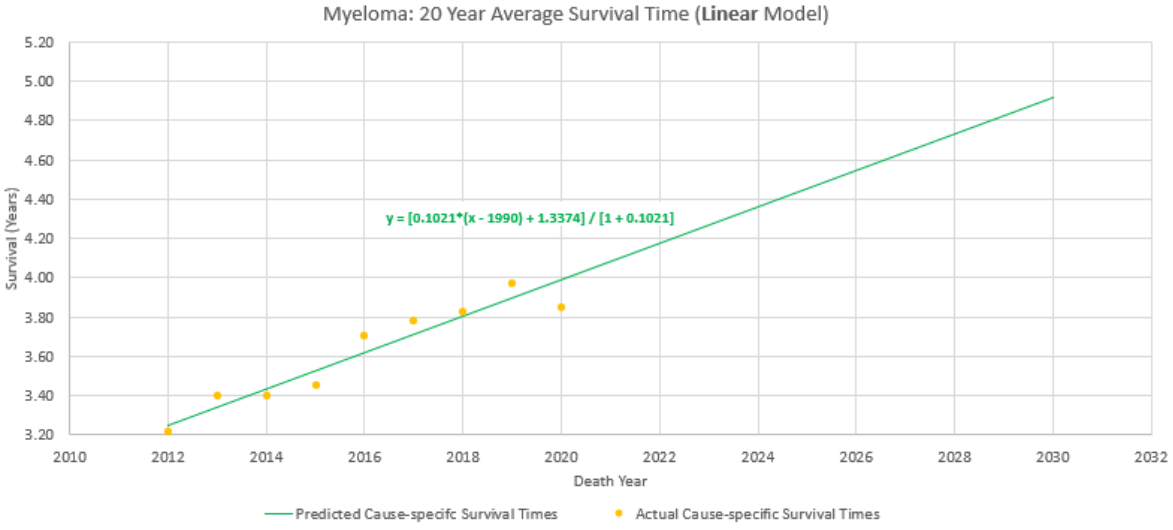


Figure 31: 20-Year Cause-specific Myeloma Avg. Survival Time Linear Model Predictions by Year of Death

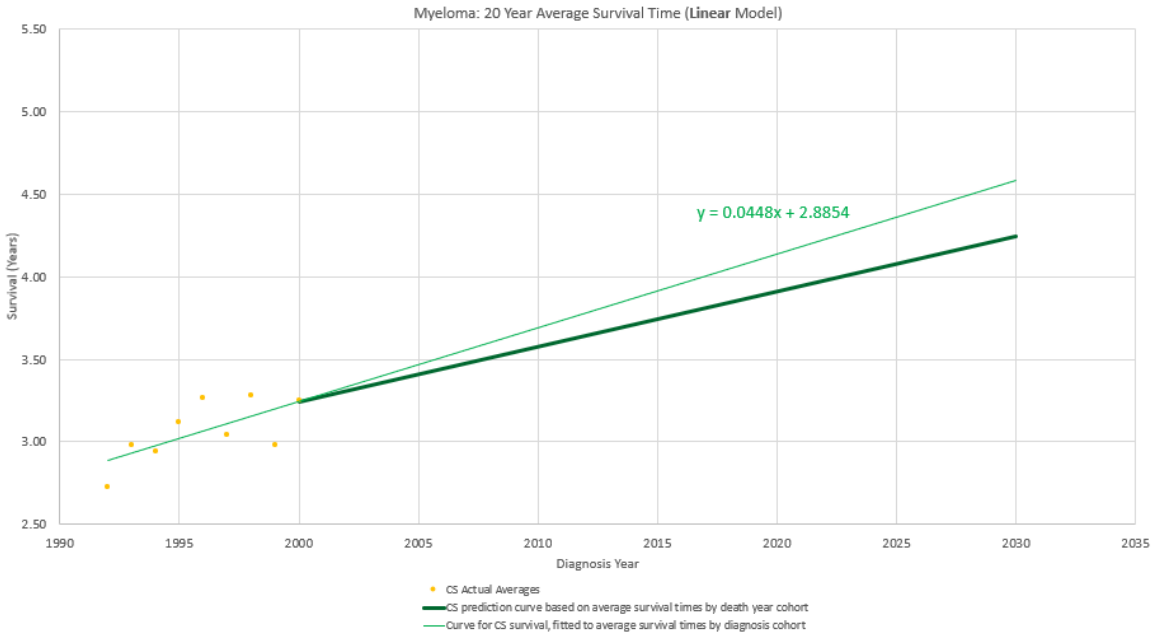


Figure 32: 20-Year Cause-specific Myeloma Avg. Survival Time Linear Model Predictions by Year of Diagnosis

4.3.3 Lung and Bronchus Cancer

5-Year Survival Time Predictions

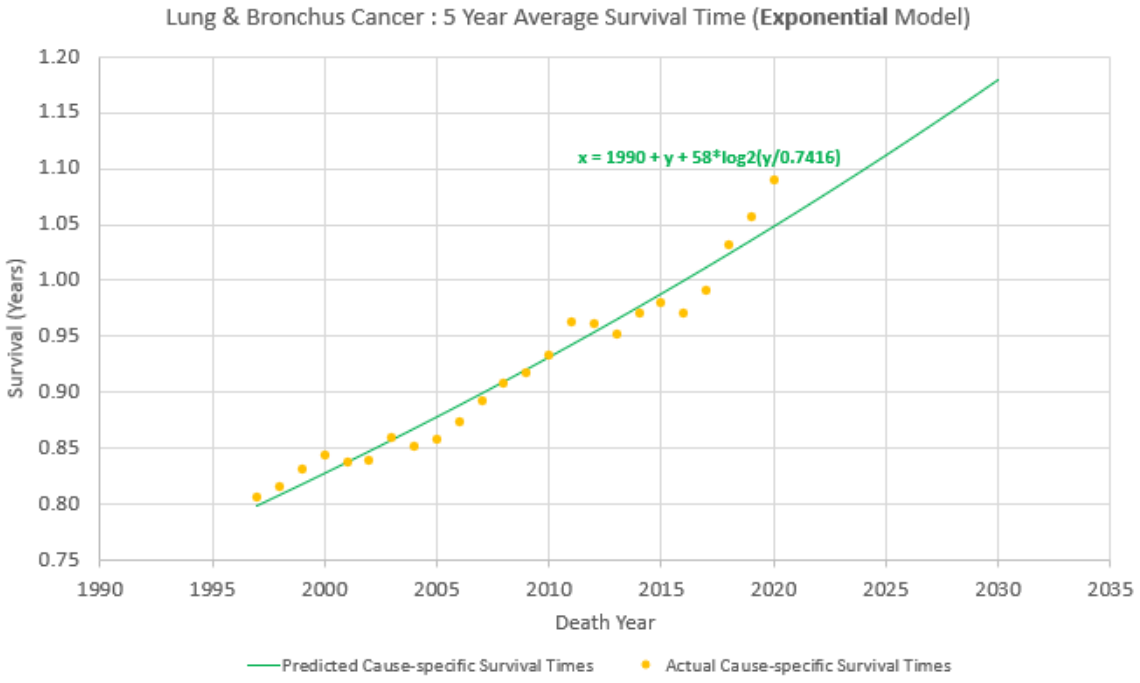


Figure 33: 5-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Exponential Model Predictions by Year of Death

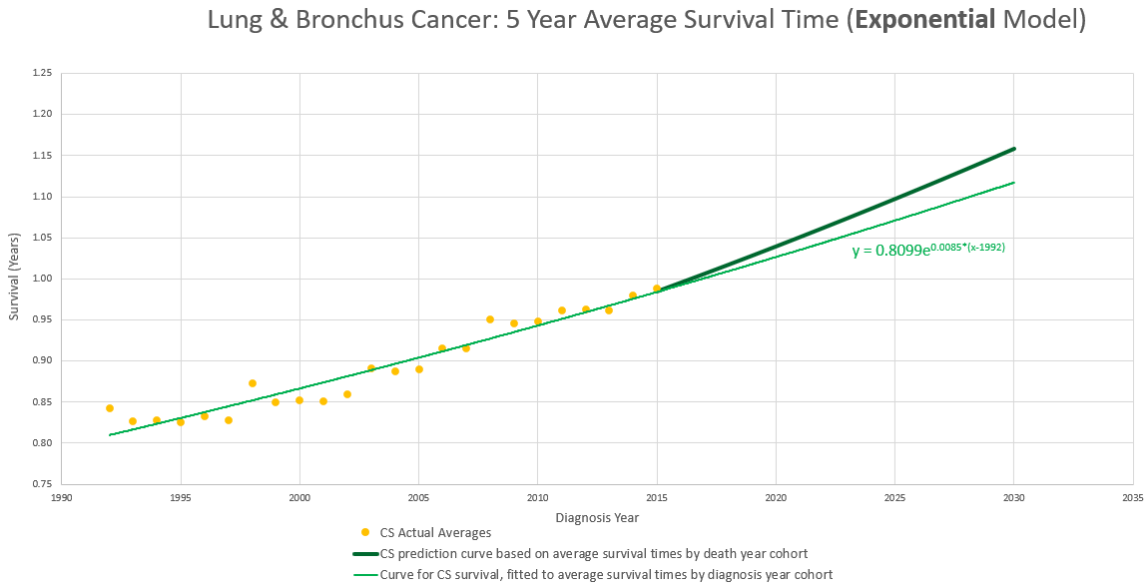


Figure 34: 5-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

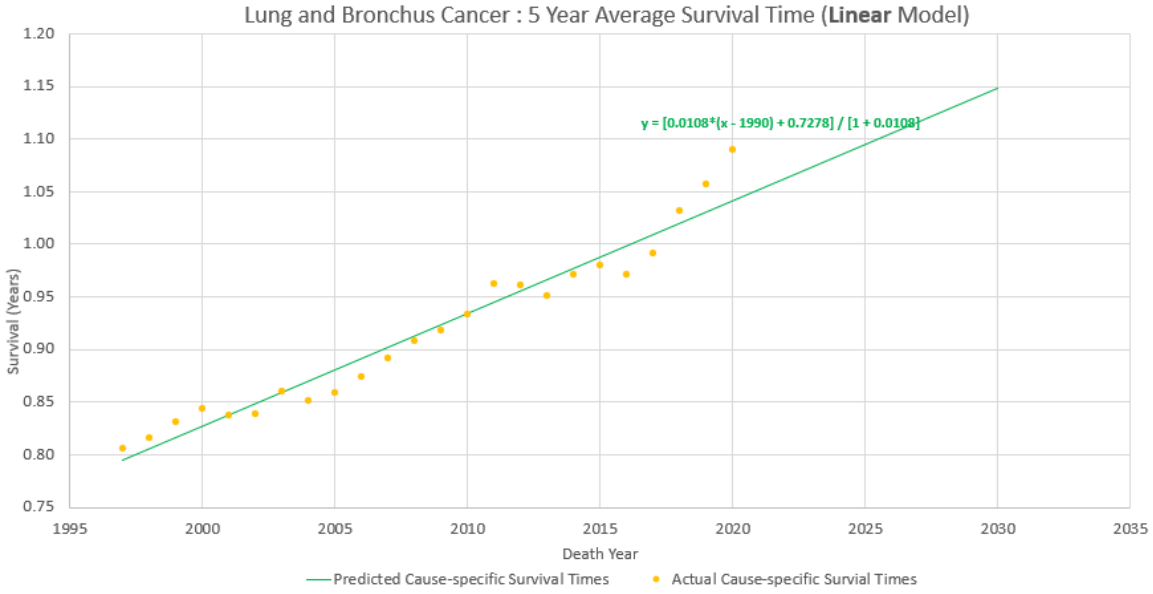


Figure 35: 5-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Linear Model Predictions by Year of Death

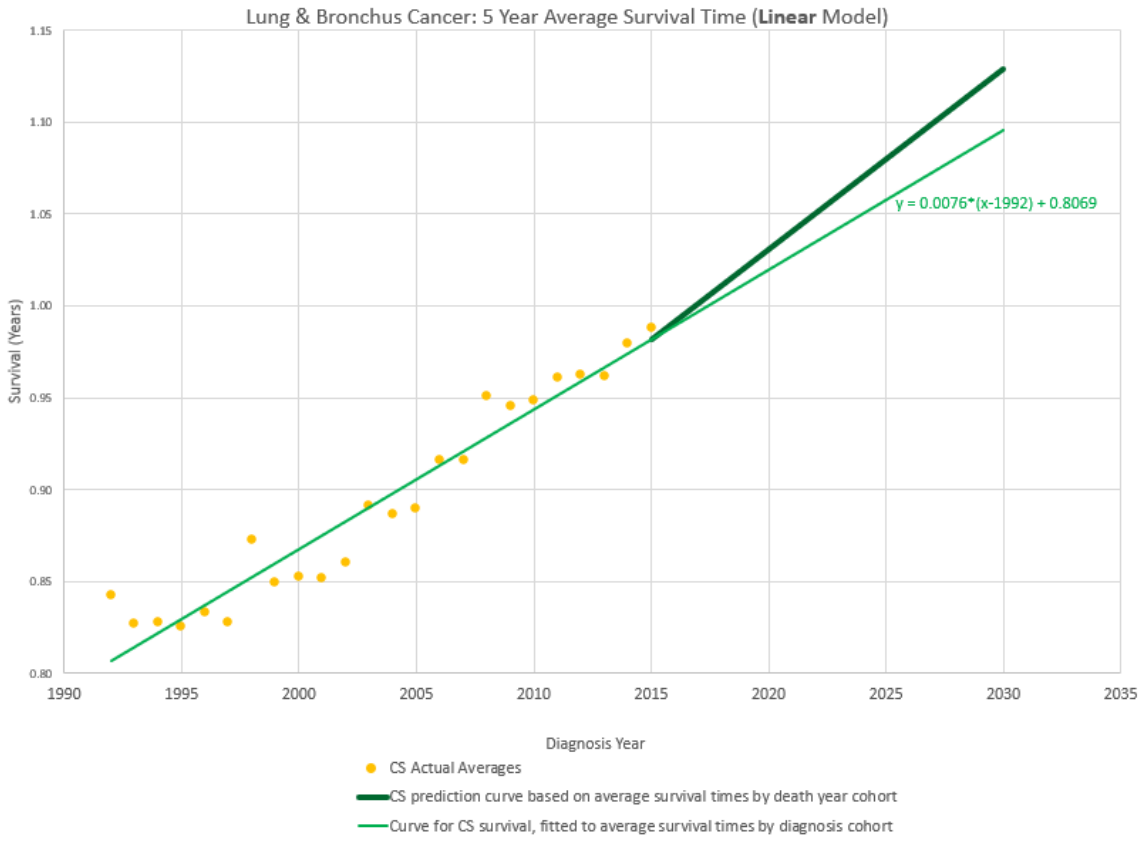


Figure 36: 5-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Linear Model Predictions by Year of Diagnosis

10-Year Survival Time Predictions

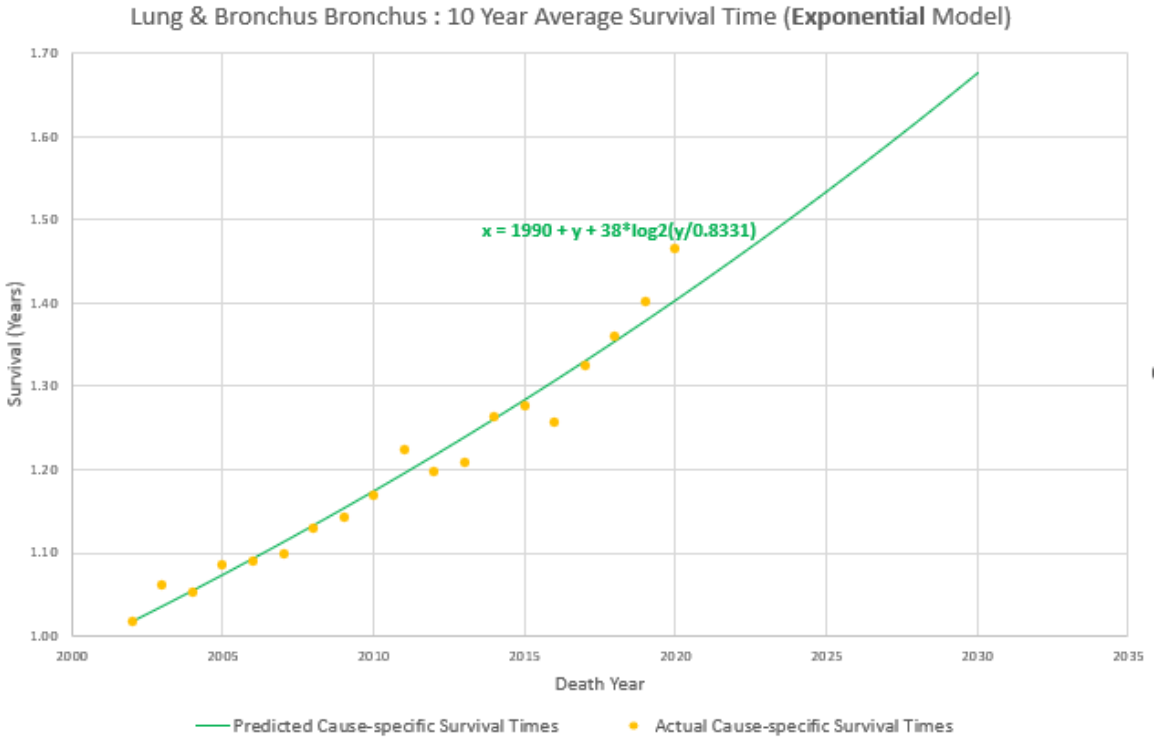


Figure 37: 10-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Exponential Model Predictions by Year of Death

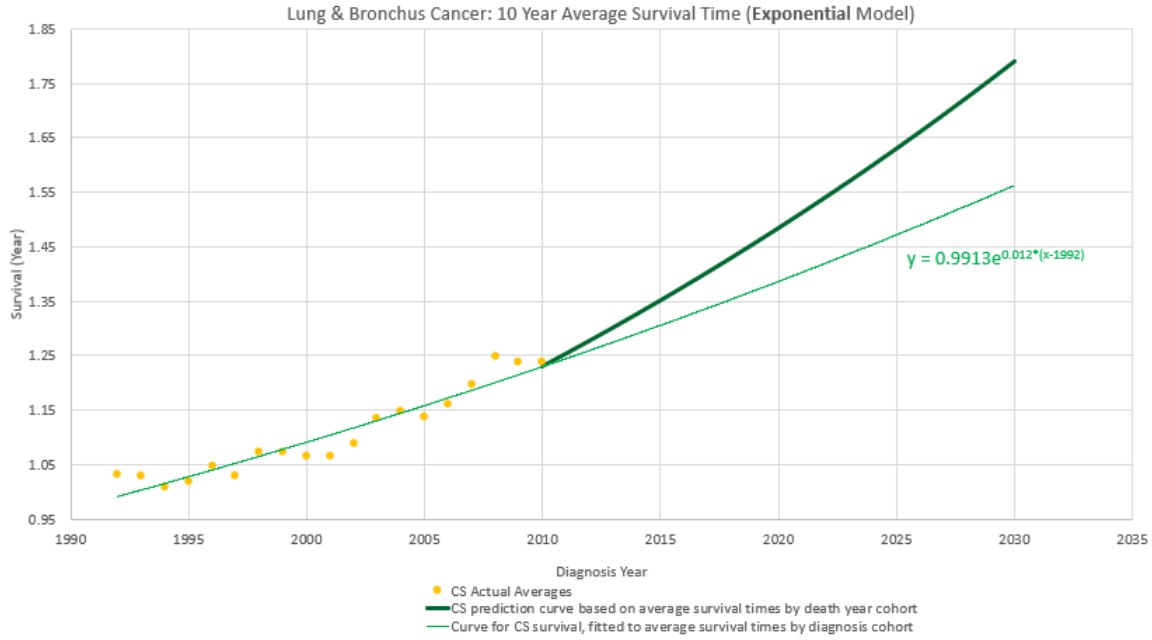


Figure 38: 10-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

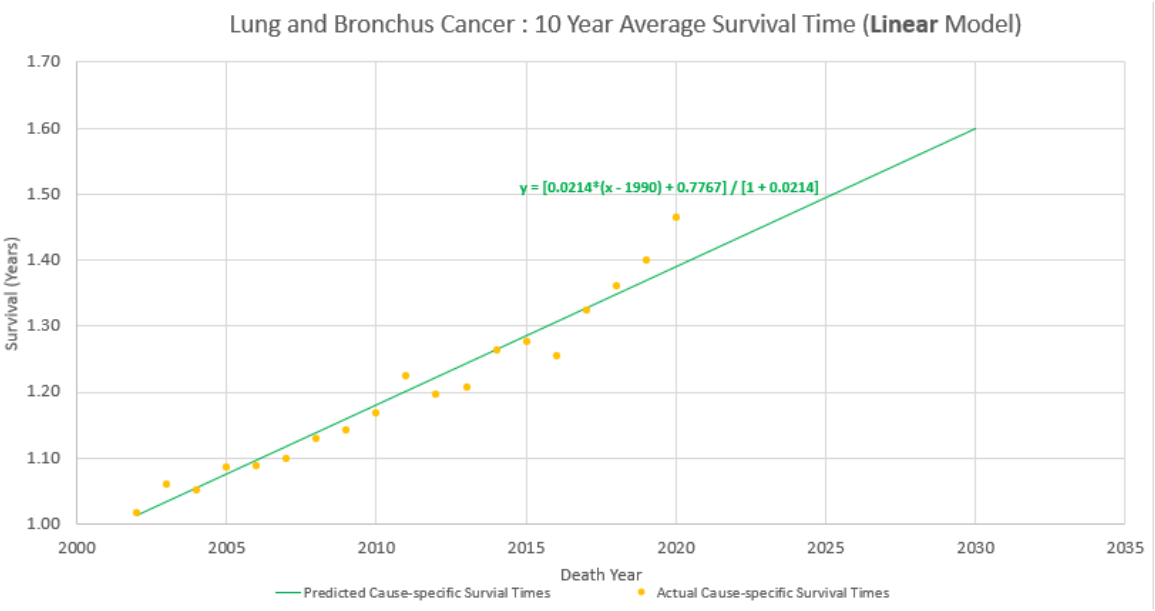


Figure 39: 10-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Linear Model Predictions by Year of Death

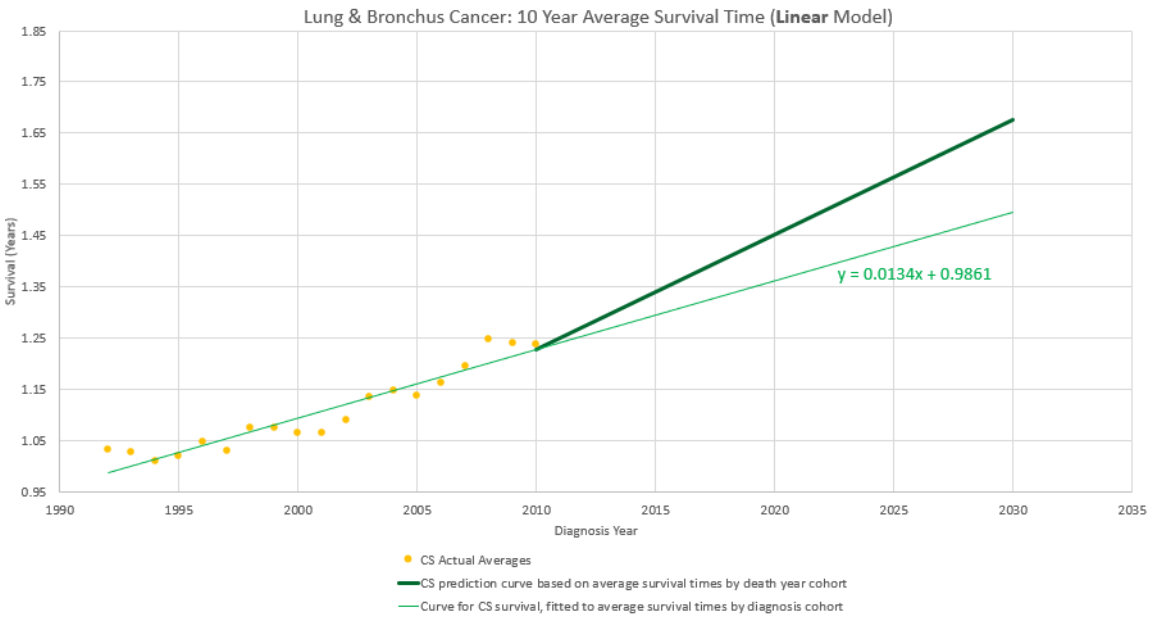


Figure 40: 10-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Linear Model Predictions by Year of Diagnosis

20-Year Survival Time Predictions

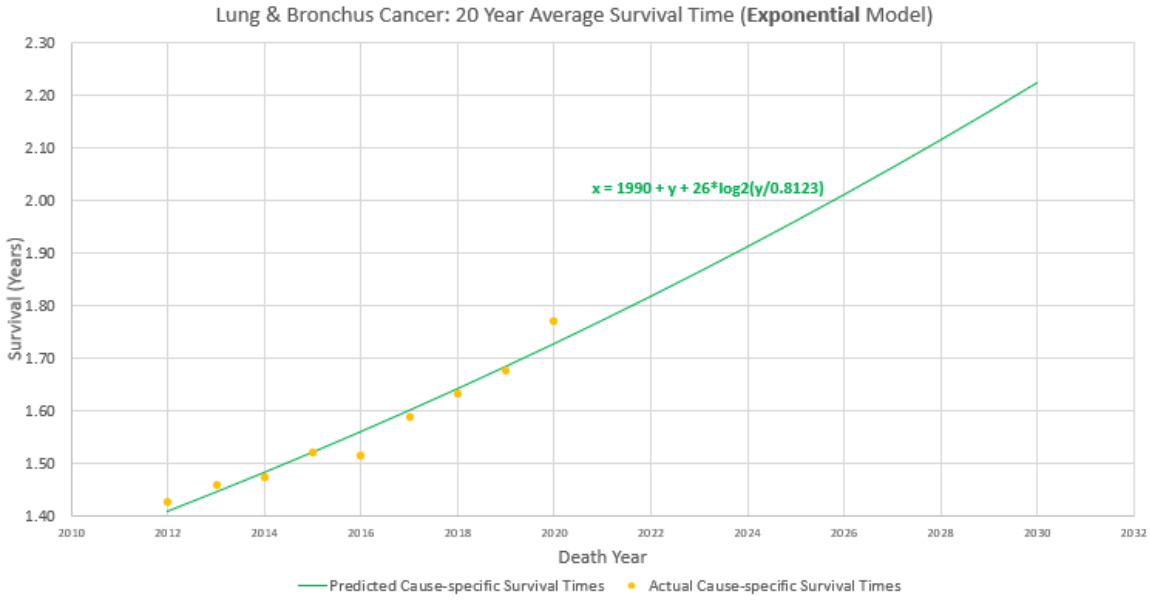


Figure 41: 20-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Exponential Model Predictions by Year of Death

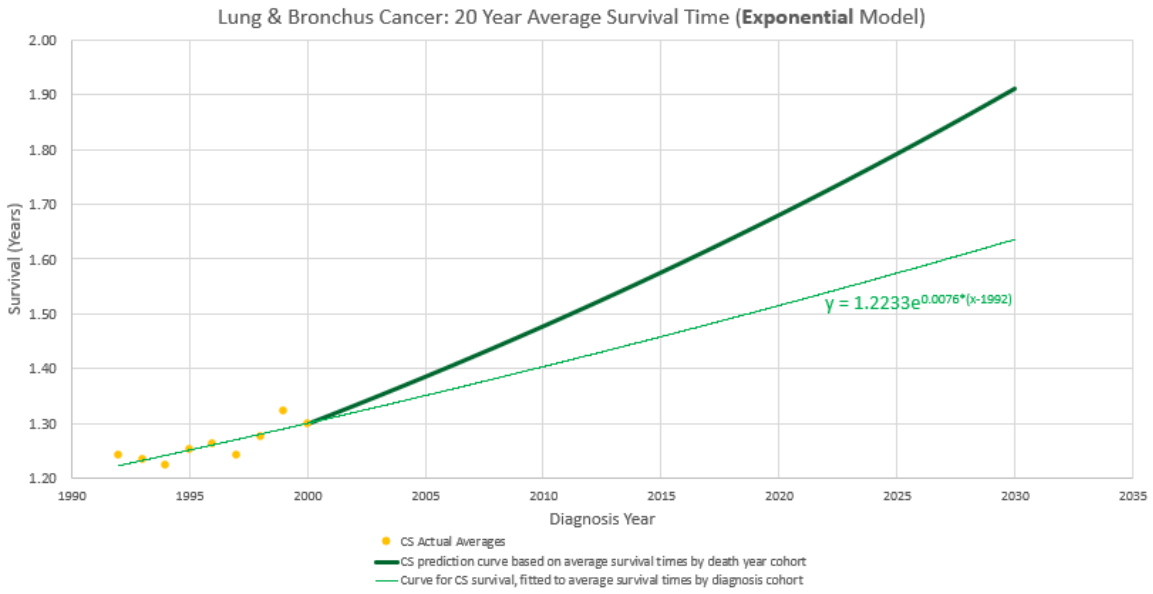


Figure 42: 20-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Exponential Model Predictions by Year of Diagnosis

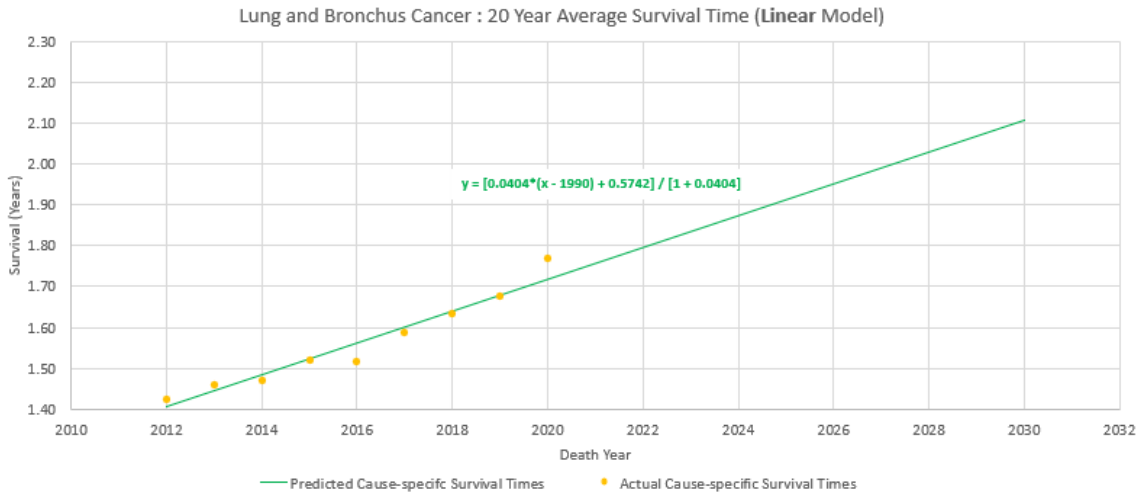


Figure 43: 20-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Linear Model Predictions by Year of Death

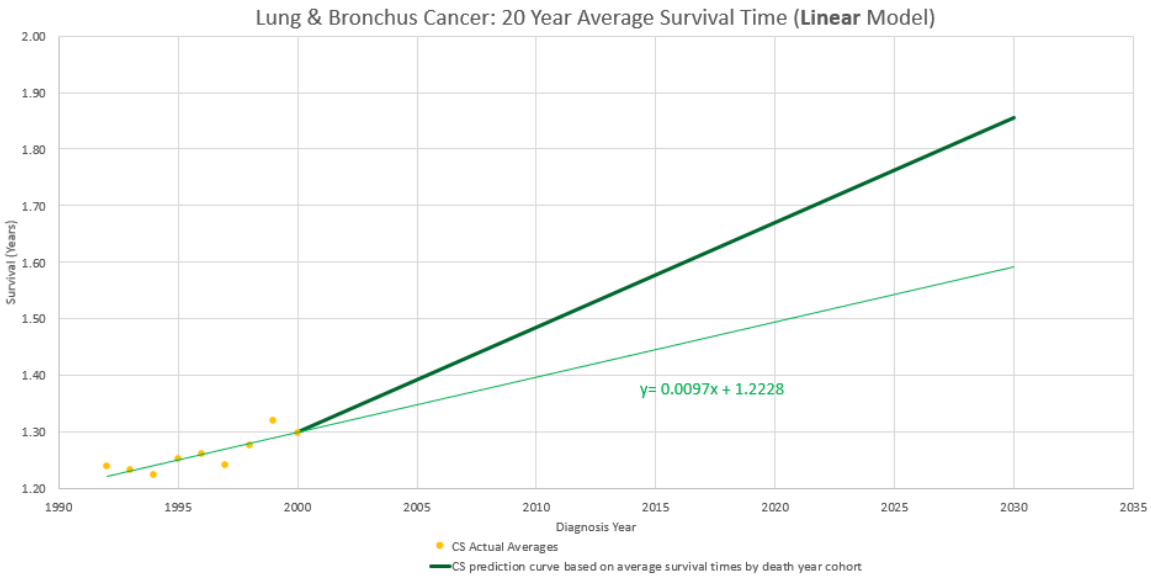


Figure 44: 20-Year Cause-specific Lung and Bronchus Cancer Avg. Survival Time Linear Model Predictions by Year of Diagnosis

5. Conclusions

Summary

Kidney and Renal Pelvis Cancer

When we compare all three survival timeframes, the 20-year survival time generally provides the best minimum SSR values across all models (table 4). The linear model provides the lowest SSR across all three survival times with a mean minimum SSR per year of 0.000712. This is lower than the mean minimum SSR's of the exponential and logistic models with SSRs of 0.001558 and 0.005062 per year respectively.

5-year average survival times of kidney and renal pelvis cancer patients generally increased from 1997 to 2020 when focusing on year of death data (appendix A1). This increase is by just under 0.24 average years of survival during the 23 year-span. It must be noted that every few years these survival time gains decline as well, but generally follow a positive trend. Survival times that focus on diagnosis year data follow a similar trend, however during the 23

years from 1992 to 2015, survival rates by diagnosis year increased even less with a 0.167 overall change (appendix A2).

5-year average survival predictions by year of death using the parameter regression-based approach generally increase over the years (figures 9, 11). Cause-specific survival times for exponential model predictions closely match actual values with minor deviations. Variability between predicted and actual values that is noticeable in specific years. Predictions by diagnosis year using the parameter regression-based and Excel hybrid approach provide slightly more optimistic survival time predictions with the difference in average survival time between the Excel predictions and the hybrid approach of approximately 0.05 average years of survival for both the linear and exponential survival models by year 2030 (figures 10, 12).

The 10-year average survival times for kidney and renal pelvis cancer had a smaller difference between the diagnosis and the death year curve findings. 10-year survival times by death year between the years 2002 to 2020 were 0.433 average years of survival, an even larger difference compared to the 5-year survival rate average prediction differences (appendix A1). On the other hand, 10-year actual survival times by diagnosis year between the years 1992 to 2010 only increased by 0.323 average years of survival, relatively low, but still improved from the 5-year actual survival rates of 0.167 average survival years (appendix A2).

10-year average survival predictions by year of death using the parameter regression-based approach generally increase using both the exponential and linear models using the parameter regression-based approach (figures 13, 15). Cause-specific survival times for exponential parameter regression-based predictions match actual values much closer than the 5-year survival case. This causes less variability between predicted and actual values for both the linear and exponential models. Hybrid model predictions by diagnosis year data provide more

optimistic survival time predictions with differences of up to 0.25 average years of survival by year 2030 for cause-specific survival times using the exponential model. The linear model predicts an even greater survival time difference, with an increase of up to 0.40 average survival years by 2030 (figures 14, 16).

The 20-year average survival times for kidney and renal pelvis cancer increased by 0.296 average years of survival from diagnosis years 1992 to 2000 (appendix A2). This is worse than the 10-year survival time difference of 0.323 average survival years between 1992 and 2010, but better than the 5-year survival time difference of 0.167 average survival years between 1992 and 2015. On the other hand, survival times by death year also decreased by 0.257 average years of survival from 2012 to 2020 (appendix A1). This is relatively close to the drop in 5-year average survival times by death year of 0.240 from 1997 to 2015, but significantly greater than the 10-year average survival time difference of 0.433 by death year from 2002 to 2010. Both survival time metrics by diagnosis year and death year depict almost flat, but still positive survival trends. It is important to note that out of all the survival times, the 20-year data had the least number of data points with only nine survival years' worth of data: 1992 to 2000 for diagnosis year data, and 2012 to 2020 for death year data.

20-year average survival predictions by year of death increased at a generally higher rate compared to actuals, similar to 5-year and 10-year averages (figures 17, 19). Perhaps due to less data availability, we see slightly more temporary decreases in average survival time predictions compared to initial predictions of both the exponential and linear models using the parameter regression-based approach. When using diagnosis year data, both the linear and exponential hybrid models showed a decrease of approximately 0.05 average survival years by year 2030 compared to the standard Excel approach (figures 18, 20).

We took SEER data and produced 5, 10, and 20-year survival parameter regression-based predictions with a maximum death year of 2030 for kidney and renal cancer patients. We compared these predictions to the new hybrid approach that we are investigating, in this case, using diagnosis year data. The hybrid approach utilizes both the parameter regression-based approach and Excel trend analysis functionality. The 5-year and 10-year survival predictions using the hybrid approach project a higher survival time than when we compare it to Excel projections for both linear and exponential models. The 20-year survival time predictions made by the hybrid approach predicts a lower survival time compared to projections using the Excel standard approach.

In summary, the average survival time for kidney and renal pelvis cancer patients shows a generally positive trend for cause-specific survival times regardless of the timeframe. The 10-year survival times seem to be the greatest followed by the 5-year survival times, and the 20-year lifetimes have the least survival time increases of the three. The linear model provides the best-fit curve describing kidney and renal pelvis survival times.

All future prediction times show a gradual increase in cause-specific survival times although to different degrees. These improvements indicate progress in healthcare management, treatment approaches, and patient support. Nevertheless, kidney and renal pelvis cancer remains a major challenge, emphasizing the need for ongoing research, early detection, innovative treatments, and comprehensive care to enhance survival rates and the quality of life for kidney and renal pelvis cancer patients.

Myeloma

When comparing all three survival timeframes, the 20-year survival time provides the best minimum SSR value for both linear and exponential models, while the best minimum SSR for the logistic model is using the 10-year data (table 5). The linear model provides the lowest

SSR across all three survival times with a mean minimum SSR per year of 0.000414933. This is lower than the mean minimum SSR's of the exponential and logistic models with SSRs of 0.000897222 and 0.003181335 per year respectively.

5-year average survival times by death year of myeloma patients have an interesting pattern that could be described as an irregular trend of increase in average survival times generally increase from 1997 to 2020 (appendix B1). When we focus particularly on death years 2001 to 2004, we would be inclined to say that the survival times are declining over time. However, during the next few years, from 2004 to 2009, myeloma survival times are increasing. More recently, between death years 2009 to 2020, one might argue that survival time differences are negligible. Holistically, between death years 1997 to 2020, we can also say the same thing as the average survival years only increased by a net of 0.065 years over those 23 years. Differences by year of diagnosis are slightly higher with a survival time increase of 0.086 years over that same time frame (appendix B2).

High levels of variability are seen between 5-year parameter regression-based predictions and actual survival times using death year data (figures 21, 23). Particularly for the exponential model, the trend takes on a more linear shape in comparison to many exponential curves. We might even say that the exponential predictions made by the parameter regression-based approach has a similar shape to the linear predictive model using the same approach. When looking at predictive models by year of diagnosis, we see similarly shaped trend lines, however, the predictions using the hybrid approach project slightly more positive future survival times from both 5-year exponential and linear predictive trends (figures 22, 24).

The 10-year average survival times of myeloma depict a slow but positive trend between death years 2002 to 2020 with a net difference in average survival time of 0.693 years (appendix

B1). Although that improvement does not seem like a lot, this is a 28.95% survival improvement within 18 years which is good. The average 10-year survival times by diagnosis year differ slightly in that from diagnosis years 1992 to 2001, the trend is very slightly positive, if not flat (appendix B2). However, from diagnosis years 2001 to 2010 survival times began to increase noticeably more year over year. This constitutes a net survival time increase of 0.87 years between diagnosis years 1997 and 2010. The majority of this average survival time increase happened after 2001. Once again, it is important to note that this is an overall average survival year increase of 36.55% in 13 years which is very positive given the relatively short time.

10-year average survival parameter regression-based predictions by year of death for the exponential model match 10-year actual values much closer than in the 5-year case, causing less variability between predicted and actual values for both the linear and the exponential models (figures 25, 27). The exponential curve is very steep but begins to show a visible curvature, while the linear model counterpart is steep as well. Predictions using the hybrid approach provide more optimistic survival times for both the exponential and linear models compared to the Excel extrapolation of the diagnosis year model (figures 26, 28).

The 20-year average myeloma survival times by death year gradually increase with a difference of 0.632 years or 19.66% between death years 1992 to 2000 (appendix B1). Unlike the 5-year and 10-year survival times, there are no decreases year over year even though some of the increases are almost negligible. Although we see fluctuations when looking at survival times by year of diagnosis, it is still a positive trend as well, with an average survival time increase of 0.520 years or 19.05% between the diagnosis years 1992 to 2000 (appendix B2).

20-year average survival parameter regression-based predictions by year of death increase at a rate similar to the 10-year averages (figures 29, 31). Due to less data availability, the

variability does increase for both the exponential and linear model predictions. Predictions made using the hybrid approach provide lower predicted survival times for both the exponential and linear models (figures 30, 32).

We took SEER data and produced 5, 10, and 20-year survival parameter regression-based predictions with a maximum death year of 2030 for myeloma patients. We compared these predictions to the new hybrid approach that we are investigating, in this case, using diagnosis year data. The hybrid approach utilizes both the parameter regression-based approach and Excel trend analysis functionality. The 5-year and 10-year survival parameter regression-based predictions projected higher survival times compared to actual data for both the linear and exponential models. The 20-year survival time parameter regression-based model predictions followed a lower survival time trend in comparison to actual data, although still positive. In summary, the current average survival times for myeloma patients by death year show a generally positive trend for 5-year, 10-year, and 20-year cause-specific survival times.

Survival time predictions by diagnosis year using the hybrid approach of both the parameter regression-based and Excel approach illustrated a more positive survival time for the 5-year and 10-year survival times, while the 20-year survival times predict a decrease over time using the hybrid. The 20-year survival times seem to be the greatest followed by the 10-year survival times, and the 5-year lifetimes have the worst survival time of the three. The linear model provides the best-fit curve for myeloma survival times.

The analyses of myeloma survival times using exponential, linear, and logistic models suggest a slower improvement in survival rates with increasing doubling times. This slow improvement in survival rates for myeloma indicates a need for further research and development of innovative treatments. Various factors such as disease complexity, late diagnosis,

genetic factors, coexisting conditions, treatment resistance, access to care, and limited treatment options may need investigation to understand if they may be contributing to this trend. Approaches for improving the prognosis and survival outcomes for myeloma patients are crucial.

Lung and Bronchus Cancer

When we compare all three survival timeframes, the 20-year survival time provides the best minimum SSR value for exponential, linear, and logistic models (table 6). The logistic model provides the lowest SSR across all three survival times with a mean minimum SSR per year of 0.000148. This is lower than the mean minimum SSR's of the exponential and linear models with SSRs of 0.0005507 and 0.000321 per year respectively.

5-year average survival times for lung and bronchus cancer patients have a visible positive trend for both data by death year and by diagnosis year. By diagnosis year we see an increase of 0.146 average years of survival or, in other words, a 17.34 % increase in 5-year average survival times between 1992 and 2015 (appendix C2). By death year we see a greater difference of 0.285 average years of survival, or 35.36% average survival time increase between 1997 and 2020 (appendix C1). That could be described as an irregular trend, although average survival times generally increased from 1997 to 2020.

5-year average survival predictions by year of death generally increase over the years. Low levels of variability are seen between parameter regression-based predictions and actual values (figures 33, 35). The exponential trend curve can be observed taking on a slight curvature. When we look at the hybrid predictive models by diagnosis year we see that both exponential and linear models using the hybrid approach project more positive survival times when compared to Excel trend projections (figures 34, 36).

The 10-year average survival times for lung and bronchus cancer patients also have a visible positive trend for both data by death year and diagnosis year. By death year we see an

increase of 0.448 average years of survival, in other words, a 44.00 % increase in 10-year average survival times between 2002 and 2020 (appendix C1). This is quite a significant increase in a relatively short amount of time. By diagnosis year, we see a slightly smaller difference of 0.205 average years of survival or 19.86% average survival time increase between the years 1997 to 2015 (appendix C2).

10-year average survival parameter regression-based predictions by year of death generally increase over the years (figures 37, 39). Similar to 5-year data, low levels of variability are once again seen between predicted and actual values. The exponential trend curve can be observed taking on a steeper curvature compared to the 5-year data. When we look at the predictive models by diagnosis year, we see that both exponential and linear models using the hybrid have significantly more positive survival times, compared to standard Excel projections (figures 38, 40).

The 20-year average survival times for lung and bronchus cancer survival times gradually increase between death years 2012 to 2020 (appendix C1). The only year a decrease is observed is between death years 2015 to 2016. For the other years, we observe a consistent increase in average survival time year over year. Overall, we see a survival time increase of 0.346 average years of survival or 24.30%. Actual survival times by diagnosis year slowly increase appearing almost stagnant as the survival time increases by only 0.058 years or 5.62% between diagnosis years 1992 to 2000 (appendix C2).

20-year average survival parameter regression-based predictions by year of death increase at rates similar to 10-year predictions (figures 41, 43). Variability does increase for both the exponential and linear model predictions likely due to less 20-year data availability. Predictions by diagnosis year using the hybrid approach provide significantly higher predicted

survival times compared to both exponential and linear models, similar to 10-year predictions (figures 42, 44).

We took SEER data and produced 5, 10, and 20-year survival parameter regression-based predictions with a maximum death year of 2030 for lung and bronchus cancer patients. We compared these predictions to the new hybrid approach that we are investigating, in this case, using diagnosis year data. The hybrid approach utilizes both the parameter regression-based approach and Excel trend analysis functionality. The 5-year and 10-year survival predictions by diagnosis using the hybrid approach all project higher survival times compared to the Excel method for both linear and exponential models. It was observed that the 20-year survival time predictions using the new approach project the highest predicted average survival time.

In summary, the average survival time for lung and bronchus cancer patients shows a generally positive trend for 5-year, 10-year, and 20-year cause-specific survival times over time. Survival times by death year show the most significant increase in survival times, while data by diagnosis year display a less dramatic, yet positive trend in survival times using the standard Excel method. Although the logistic model provides the best-fit curve for lung and bronchus cancer survival times, of the two models we use for comparing with the traditional method using Excel, the linear model fits best to the lung and bronchus data.

Analysis for lung and bronchus cancer survival times using exponential, linear, and logistic models suggest survival times for lung and bronchus cancer have been gradually improving over time. This perhaps may be due to advancements in early detection, better treatment options, and enhanced patient care. To continue this progress, it is essential to increase awareness and prevention measures, such as anti-smoking campaigns, and to invest in research for new and more effective treatments. Enhancing early detection methods through improved

screening programs, providing better access to healthcare, and supporting personalized medicine tailored to individual patient needs are also crucial steps in further improving survival rates.

Prostate Cancer

5-year average survival times for prostate cancer patient survival projections are not provided here. Prostate cancer was found to have decreasing average survival times, which was not anticipated for this study. The code created to support the methodology of the new approach does not search for negative slope values, and so the analysis was out of scope for this paper. Regardless, we investigated further to better understand what the prostate cancer data may tell us.

We learned a few things. For example, in Table 8 we see that although the number of patients diagnosed each year is relatively high, the proportion of them who pass away annually is relatively low. Table 9 further tells us that the proportion of deaths have generally dropped from diagnosis years 1992 to 2009, however beginning 2010 to 2015 there has been an increase in prostate cancer deaths. This finding is quite interesting as prostate cancer is frequently screened for in at-risk populations and is generally considered a treatable disease when diagnosed early.

We produced Table 10 to help us further understand these findings. This table takes those death percentages and allows us to see the average lost years of life by the fifth year after diagnosis year. Figure 7 helps us visualize the fifth year and other years. The difference in survival rates is used to mathematically determine the average per patient-years lost by the end of year five following initial diagnosis, illustrated in Figure 8.

Breast Cancer

Similar to prostate cancer, breast cancer findings are distinct from other cancers in this study as the survival times suggest a potential stagnation or decline in more recent periods that could be explored further like we did prostate cancer. In addition to breast cancer having high

incidence and low death rates, these findings could correlate with external factors such as economic downturns, public health crises, or changes in healthcare policy affecting mortality. Further analysis could explore the specific causes underlying the cause-specific rates and investigate additional factors influencing the observed trends.

Future Works

Although this paper produces useful insights there is more work to be done. The SEER data that was extracted was by year of death and year of diagnosis, but it does not consider months or days. For example, if a patient were diagnosed in December 2012, and passed away in February 2013, this would be counted as a survival time of 1 year, when it was much less than that at 2 months, possibly less if counting by days. If we were able to account for such times more accurately, this would give a more accurate picture of cancer patient deaths although there is little reason to believe it would have a significant impact on results.

It would also be useful to analyze and predict survival times for cancers or other entities that have decreasing survival times. Unfortunately, although it is generally assumed that all cancer types have increasing survival times over time due to increasing knowledge and technological innovations, this is not necessarily always the case. We saw indications of this possibility with breast and prostate cancers. The methodologies used in this study are currently unable to handle this scenario, which caused some cancer types to be left not fully analyzed.

Given the methodologies used in this paper, logistic model predictions were not computed. It would be not only interesting, but valuable as well to have and assess logistic model predictions and compare those findings with linear and exponential predictive findings. To do so, we would need to use the Solver plug-in from Microsoft Excel or some other similar software.

Other models currently found in the Excel trend analysis functionality could also be tested on our data set.

As we saw with prostate cancer, the survival time calculation we use in this study may need to be updated to reflect similar cancers that have high incidence rates, but low death rates. For cancers such as these, the survival metric we use is misleading and often understated which could lead to clinicians and patients being misinformed on how these cancers are truly trending. Having a more reliable calculation will help drive recommended treatment plans, as well as patient treatment plan decision-making.

Discussion

This paper explores survival times using SEER 12 data. This dataset includes 12 registries throughout the United States and covers 12.2% of the United States population encompassing over five million registered cancer cases in the United States between the years 1992 and 2020. Using SEER data, average survival time trends were produced using the year of diagnosis and year of death data and compared across linear and exponential curves to identify and explain the survival times and trends for each respective cancer.

The average survival time for kidney and renal pelvis cancer patients shows a generally positive trend for cause-specific survival times regardless of the timeframe. The linear model best describes the survival times of kidney and renal pelvis cancer patients. Both linear and exponential hybrid models predict increased average survival times for 5 and 10-year survival horizons compared to Excel models. 20-year predictive survival using the hybrid method forecasts lower average years of survival times compared to Excel for both the linear and exponential models.

The average survival time for myeloma patients shows a positive trend for cause-specific survival times regardless of the timeframe. The linear model best describes the survival lifetime of myeloma. Similar to kidney and renal pelvis cancer, both hybrid linear and exponential predictive models that incorporate more recent year of death data predict increased average survival times for 5-year and 10-year survival horizons compared to the Excel method. 20-year predictive survival times using the hybrid method forecasts lower average years of survival times compared to Excel for both the linear and exponential models.

The average survival times for lung and bronchus cancer patients shows a generally positive trend for 5-year, 10-year, and 20-year cause-specific observation periods over time. Although the logistic model provides the best-fit curve to lung and bronchus cancer survival times, the linear model fits best to the lung and bronchus data. The 5-year and 10-year survival predictions by diagnosis year using the hybrid approach all project higher survival times compared to Excel for both the linear and exponential models. It was observed that the 20-year survival time predictions using the hybrid approach project the highest average predicted survival time.

Although the prostate and breast cancer findings were unexpected, they provided us with the opportunity to see that there is a group of cancer types that have unusual survival time characteristics. These may be temporary, but still need further investigation.

This paper explores survival times of kidney and renal, myeloma, lung and bronchus, prostate and breast cancer patients using November 2022 submission SEER 12 data. We discovered that our hybrid model may help us better understand the survival trends of cancers with high incidence and high death rates such as kidney and renal cancer, myeloma, as well as lung and bronchus cancers. Other cancers with high incidences and low death rates led to

unexpected results, however, they could be addressed using our method by choosing to use more informative data as well as by extending our method to handle trends of decrease as well as logistic modeling.

Appendix

A. Kidney and Renal Pelvis Cancer Raw Data

1. By Death Year

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 1997 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	5	1997	39
1993	4	1997	56
1994	3	1997	66
1995	2	1997	151
1996	1	1997	328
1997	0	1997	438

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 1998 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1993	5	1998	47
1994	4	1998	58
1995	3	1998	74
1996	2	1998	144
1997	1	1998	362
1998	0	1998	472

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 1999 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1994	5	1999	53
1995	4	1999	67
1996	3	1999	85
1997	2	1999	139
1998	1	1999	338

1999	0	1999	469

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2000 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	5	2000	40
1996	4	2000	54
1997	3	2000	96
1998	2	2000	152
1999	1	2000	333
2000	0	2000	452

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2001 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	5	2001	38
1997	4	2001	40
1998	3	2001	87
1999	2	2001	142
2000	1	2001	340
2001	0	2001	451

The remaining 5-year tables are embedded in the tables below.

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2002 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	10	2002	23
1993	9	2002	26
1994	8	2002	26
1995	7	2002	32
1996	6	2002	30
1997	5	2002	48
1998	4	2002	63
1999	3	2002	84
2000	2	2002	158

2001	1	2002	327
2002	0	2002	473

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2003 - 10 Year

Dx. Year	**Lifetime**	**Death Year**	**N**
1993	10	2003	14
1994	9	2003	31
1995	8	2003	18
1996	7	2003	25
1997	6	2003	36
1998	5	2003	47
1999	4	2003	63
2000	3	2003	101
2001	2	2003	177
2002	1	2003	341
2003	0	2003	474

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2004 - 10 Year

Dx. Year	**Lifetime**	**Death Year**	**N**
1994	10	2004	19
1995	9	2004	26
1996	8	2004	26
1997	7	2004	32
1998	6	2004	40
1999	5	2004	51
2000	4	2004	60
2001	3	2004	95
2002	2	2004	149
2003	1	2004	367
2004	0	2004	463

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2005 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	10	2005	26
1996	9	2005	21
1998	8	2005	26
1999	7	2005	33
2000	6	2005	40
2001	5	2005	64
2002	4	2005	73
2003	3	2005	74
2004	2	2005	172
2005	1	2005	323
2006	0	2005	466

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2006 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	10	2006	21
1997	9	2006	17
1998	8	2006	19
1999	7	2006	32
2000	6	2006	39
2001	5	2006	48
2002	4	2006	71
2003	3	2006	92
2004	2	2006	163
2005	1	2006	337
2006	0	2006	454

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2007 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**

1997	10	2007	19
1998	9	2007	30
1999	8	2007	28
2000	7	2007	37
2001	6	2007	40
2002	5	2007	53
2003	4	2007	99
2004	3	2007	129
2005	2	2007	152
2006	1	2007	353
2007	0	2007	497

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2008 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1998	10	2008	21
1999	9	2008	24
2000	8	2008	29
2001	7	2008	30
2002	6	2008	62
2003	5	2008	53
2004	4	2008	65
2005	3	2008	93
2006	2	2008	189
2007	1	2008	366
2008	0	2008	477

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2009 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1999	10	2009	26
2000	9	2009	23
2001	8	2009	26
2002	7	2009	39
2003	6	2009	48
2004	5	2009	60

2005	4	2009	63
2006	3	2009	93
2007	2	2009	156
2008	1	2009	377
2009	0	2009	440

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2010 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2000	10	2010	28
2001	9	2010	24
2002	8	2010	43
2003	7	2010	34
2004	6	2010	61
2005	5	2010	48
2006	4	2010	81
2007	3	2010	96
2008	2	2010	178
2009	1	2010	387
2010	0	2010	447

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2011 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2001	10	2011	31
2002	9	2011	22
2003	8	2011	27
2004	7	2011	50
2005	6	2011	63
2006	5	2011	64
2007	4	2011	97
2008	3	2011	113
2009	2	2011	179
2010	1	2011	384
2011	0	2011	450

The remaining 5-year and 10-year tables are embedded in the tables below.

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2012 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	20	2012	9
1993	19	2012	6
1994	18	2012	21
1995	17	2012	12
1996	16	2012	9
1997	15	2012	12
1998	14	2012	21
1999	13	2012	13
2000	12	2012	18
2001	11	2012	34
2002	10	2012	20
2003	9	2012	41
2004	8	2012	54
2005	7	2012	43
2006	6	2012	51
2007	5	2012	75
2008	4	2012	94
2009	3	2012	120
2010	2	2012	161
2011	1	2012	403
2012	0	2012	469

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2013 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1993	20	2013	7
1994	19	2013	7
1995	18	2013	7
1996	17	2013	6
1997	16	2013	13
1998	15	2013	17
1999	14	2013	9
2000	13	2013	21
2001	12	2013	28
2002	11	2013	23
2003	10	2013	31

2004	9	2013	30
2005	8	2013	41
2006	7	2013	44
2007	6	2013	55
2008	5	2013	84
2009	4	2013	61
2010	3	2013	103
2011	2	2013	170
2012	1	2013	399
2013	0	2013	428

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2014 - 20 Year

Dx. Year	**Lifetime**	**Death Year**	**N**
1994	20	2014	4
1995	19	2014	8
1996	18	2014	10
1997	17	2014	9
1998	16	2014	10
1999	15	2014	14
2000	14	2014	16
2001	13	2014	27
2002	12	2014	28
2003	11	2014	27
2004	10	2014	23
2005	9	2014	40
2006	8	2014	43
2007	7	2014	50
2008	6	2014	47
2009	5	2014	71
2010	4	2014	94
2011	3	2014	130
2012	2	2014	171
2013	1	2014	393
2014	0	2014	494

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2015 - 20 Year

Dx. Year	Lifetime	Death Year	N
1995	20	2015	7
1996	19	2015	11
1997	18	2015	7
1998	17	2015	12
1999	16	2015	14
2000	15	2015	14
2001	14	2015	14
2002	13	2015	18
2003	12	2015	26
2004	11	2015	32
2005	10	2015	44
2006	9	2015	27
2007	8	2015	48
2008	7	2015	66
2009	6	2015	71
2010	5	2015	84
2011	4	2015	100
2012	3	2015	128
2013	2	2015	204
2014	1	2015	393
2015	0	2015	514

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2016 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	20	2016	10
1997	19	2016	10
1998	18	2016	8
1999	17	2016	17
2000	16	2016	22
2001	15	2016	14
2002	14	2016	14
2003	13	2016	26
2004	12	2016	31
2005	11	2016	42
2006	10	2016	47
2007	9	2016	40
2008	8	2016	48
2009	7	2016	35

2010	6	2016	49
2011	5	2016	62
2012	4	2016	100
2013	3	2016	121
2014	2	2016	195
2015	1	2016	373
2016	0	2016	508

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2017 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1997	20	2017	8
1998	19	2017	7
1999	18	2017	15
2000	17	2017	16
2001	16	2017	15
2002	15	2017	16
2003	14	2017	17
2004	13	2017	21
2005	12	2017	26
2006	11	2017	34
2007	10	2017	38
2008	9	2017	40
2009	8	2017	35
2010	7	2017	53
2011	6	2017	54
2012	5	2017	69
2013	4	2017	102
2014	3	2017	127
2015	2	2017	184
2016	1	2017	373
2017	0	2017	459

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2018 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1998	20	2018	8

1999	19	2018	14
2000	18	2018	17
2001	17	2018	11
2002	16	2018	16
2003	15	2018	15
2004	14	2018	27
2005	13	2018	25
2006	12	2018	26
2007	11	2018	43
2008	10	2018	34
2009	9	2018	44
2010	8	2018	36
2011	7	2018	61
2012	6	2018	60
2013	5	2018	66
2014	4	2018	92
2015	3	2018	131
2016	2	2018	179
2017	1	2018	405
2018	0	2018	433

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2019 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1999	20	2019	15
2000	19	2019	7
2001	18	2019	13
2002	17	2019	14
2003	16	2019	15
2004	15	2019	22
2005	14	2019	30
2006	13	2019	28
2007	12	2019	24
2008	11	2019	34
2009	10	2019	34
2010	9	2019	33
2011	8	2019	65
2012	7	2019	52
2013	6	2019	72

2014	5	2019	73
2015	4	2019	91
2016	3	2019	121
2017	2	2019	193
2018	1	2019	319
2019	0	2019	473

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients in 2020 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2000	20	2020	15
2001	19	2020	8
2002	18	2020	8
2003	17	2020	13
2004	16	2020	12
2005	15	2020	25
2006	14	2020	25
2007	13	2020	27
2008	12	2020	28
2009	11	2020	29
2010	10	2020	35
2011	9	2020	36
2012	8	2020	53
2013	7	2020	53
2014	6	2020	60
2015	5	2020	68
2016	4	2020	101
2017	3	2020	130
2018	2	2020	191
2019	1	2020	365
2020	0	2020	492

2. By Diagnosis Year

5-year and 10-year tables are embedded in the tables below.

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1992 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1992	0	1992	377

1993	1	1992	312
1994	2	1992	129
1995	3	1992	72
1996	4	1992	42
1997	5	1992	39
1998	6	1992	34
1999	7	1992	30
2000	8	1992	25
2001	9	1992	22
2002	10	1992	23
2003	11	1992	16
2004	12	1992	15
2005	13	1992	17
2006	14	1992	6
2007	15	1992	17
2008	16	1992	10
2009	17	1992	12
2010	18	1992	7
2011	19	1992	7
2012	20	1992	9

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1993 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1993	0	1993	376
1994	1	1993	322
1995	2	1993	132
1996	3	1993	101
1997	4	1993	56
1998	5	1993	47
1999	6	1993	21
2000	7	1993	29
2001	8	1993	24
2002	9	1993	26
2003	10	1993	14
2004	11	1993	16
2005	12	1993	19
2006	13	1993	17
2007	14	1993	11
2008	15	1993	6
2009	16	1993	11
2010	17	1993	5

2011	18	1993	8
2012	19	1993	6
2013	20	1993	7

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1994 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1994	0	1994	395
1995	1	1994	298
1996	2	1994	117
1997	3	1994	66
1998	4	1994	58
1999	5	1994	53
2000	6	1994	38
2001	7	1994	28
2002	8	1994	26
2003	9	1994	31
2004	10	1994	19
2005	11	1994	12
2006	12	1994	15
2007	13	1994	20
2008	14	1994	17
2009	15	1994	10
2010	16	1994	10
2011	17	1994	11
2012	18	1994	21
2013	19	1994	7
2014	20	1994	4

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1995 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1995	0	1995	401
1996	1	1995	323
1997	2	1995	151
1998	3	1995	74
1999	4	1995	67
2000	5	1995	40
2001	6	1995	38
2002	7	1995	32

2003	8	1995	18
2004	9	1995	26
2005	10	1995	26
2006	11	1995	19
2007	12	1995	18
2008	13	1995	7
2009	14	1995	11
2010	15	1995	11
2011	16	1995	11
2012	17	1995	12
2013	18	1995	7
2014	19	1995	8
2015	20	1995	7

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1996 - 20 Year

Death Yr.	**Lifetime**	**Dx. Year**	**N**
1996	0	1996	441
1997	1	1996	328
1998	2	1996	144
1999	3	1996	85
2000	4	1996	54
2001	5	1996	38
2002	6	1996	30
2003	7	1996	25
2004	8	1996	26
2005	9	1996	21
2006	10	1996	21
2007	11	1996	13
2008	12	1996	18
2009	13	1996	12
2010	14	1996	18
2011	15	1996	7
2012	16	1996	9
2013	17	1996	6
2014	18	1996	10
2015	19	1996	11
2016	20	1996	10

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1997 - 20 Year

Death Yr.	Lifetime	Dx. Year	N
1997	0	1997	438
1998	1	1997	362
1999	2	1997	139
2000	3	1997	96
2001	4	1997	40
2002	5	1997	48
2003	6	1997	36
2004	7	1997	32
2005	8	1997	26
2006	9	1997	17
2007	10	1997	19
2008	11	1997	15
2009	12	1997	21
2010	13	1997	13
2011	14	1997	18
2012	15	1997	12
2013	16	1997	13
2014	17	1997	9
2015	18	1997	7
2016	19	1997	10
2017	20	1997	8

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1998 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1998	0	1998	472
1999	1	1998	338
2000	2	1998	152
2001	3	1998	87
2002	4	1998	63
2003	5	1998	47
2004	6	1998	40
2005	7	1998	33
2006	8	1998	19
2007	9	1998	30
2008	10	1998	21
2009	11	1998	15
2010	12	1998	12
2011	13	1998	18
2012	14	1998	21

2013	15	1998	17
2014	16	1998	10
2015	17	1998	12
2016	18	1998	8
2017	19	1998	7
2018	20	1998	8

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 1999 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1999	0	1999	469
2000	1	1999	333
2001	2	1999	142
2002	3	1999	84
2003	4	1999	63
2004	5	1999	51
2005	6	1999	40
2006	7	1999	32
2007	8	1999	28
2008	9	1999	24
2009	10	1999	26
2010	11	1999	12
2011	12	1999	20
2012	13	1999	13
2013	14	1999	9
2014	15	1999	14
2015	16	1999	14
2016	17	1999	17
2017	18	1999	15
2018	19	1999	14
2019	20	1999	15

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2000 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2000	0	2000	452
2001	1	2000	340
2002	2	2000	158
2003	3	2000	101
2004	4	2000	60

2005	5	2000	64
2006	6	2000	39
2007	7	2000	37
2008	8	2000	29
2009	9	2000	23
2010	10	2000	28
2011	11	2000	20
2012	12	2000	18
2013	13	2000	21
2014	14	2000	16
2015	15	2000	14
2016	16	2000	22
2017	17	2000	16
2018	18	2000	17
2019	19	2000	7
2020	20	2000	15

5-year tables are embedded in the tables below.

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2001 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2001	0	2001	451
2002	1	2001	327
2003	2	2001	177
2004	3	2001	95
2005	4	2001	73
2006	5	2001	48
2007	6	2001	40
2008	7	2001	30
2009	8	2001	26
2010	9	2001	24
2011	10	2001	31

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2002 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2002	0	2002	473
2003	1	2002	341
2004	2	2002	149

2005	3	2002	74
2006	4	2002	71
2007	5	2002	53
2008	6	2002	62
2009	7	2002	39
2010	8	2002	43
2011	9	2002	22
2012	10	2002	20

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2003 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2003	0	2003	474
2004	1	2003	367
2005	2	2003	172
2006	3	2003	92
2007	4	2003	99
2008	5	2003	53
2009	6	2003	48
2010	7	2003	34
2011	8	2003	27
2012	9	2003	41
2013	10	2003	31

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2004 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2004	0	2004	463
2005	1	2004	323
2006	2	2004	163
2007	3	2004	129
2008	4	2004	65
2009	5	2004	60
2010	6	2004	61
2011	7	2004	50
2012	8	2004	54
2013	9	2004	30
2014	10	2004	23

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2005 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2005	0	2005	466
2006	1	2005	337
2007	2	2005	152
2008	3	2005	93
2009	4	2005	63
2010	5	2005	48
2011	6	2005	63
2012	7	2005	43
2013	8	2005	41
2014	9	2005	40
2015	10	2005	44

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2006 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2006	0	2006	454
2007	1	2006	353
2008	2	2006	189
2009	3	2006	93
2010	4	2006	81
2011	5	2006	64
2012	6	2006	51
2013	7	2006	44
2014	8	2006	43
2015	9	2006	27
2016	10	2006	47

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2007 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2007	0	2007	497
2008	1	2007	366
2009	2	2007	156
2010	3	2007	96
2011	4	2007	97
2012	5	2007	75

2013	6	2007	55
2014	7	2007	50
2015	8	2007	48
2016	9	2007	40
2017	10	2007	38

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2008 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2008	0	2008	477
2009	1	2008	377
2010	2	2008	178
2011	3	2008	113
2012	4	2008	94
2013	5	2008	84
2014	6	2008	47
2015	7	2008	66
2016	8	2008	48
2017	9	2008	40
2018	10	2008	34

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2009 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2009	0	2009	440
2010	1	2009	387
2011	2	2009	179
2012	3	2009	120
2013	4	2009	61
2014	5	2009	71
2015	6	2009	71
2016	7	2009	35
2017	8	2009	35
2018	9	2009	44
2019	10	2009	34

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2010 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**

2010	0	2010	447
2011	1	2010	384
2012	2	2010	161
2013	3	2010	103
2014	4	2010	94
2015	5	2010	84
2016	6	2010	49
2017	7	2010	53
2018	8	2010	36
2019	9	2010	33
2020	10	2010	35

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2011 - 5 Year			
Death Yr.	Lifetime	Dx. Year	N
2011	0	2011	450
2012	1	2011	403
2013	2	2011	170
2014	3	2011	130
2015	4	2011	100
2016	5	2011	62

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2012 - 5 Year			
Death Yr.	Lifetime	Dx. Year	N
2012	0	2012	469
2013	1	2012	399
2014	2	2012	171
2015	3	2012	128
2016	4	2012	100
2017	5	2012	69

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2013 - 5 Year			
Death Yr.	Lifetime	Dx. Year	N
2013	0	2013	428
2014	1	2013	393
2015	2	2013	204

2016	3	2013	121
2017	4	2013	102
2018	5	2013	66

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2014 - 5 Year			
Death Yr.	Lifetime	Dx. Year	N
2014	0	2014	494
2015	1	2014	393
2016	2	2014	195
2017	3	2014	127
2018	4	2014	92
2019	5	2014	73

Number of Cause-Specific Deaths of Kidney and Renal Cancer Patients Diagnosed in 2015 - 5 Year			
Death Yr.	Lifetime	Dx. Year	N
2015	0	2015	514
2016	1	2015	373
2017	2	2015	184
2018	3	2015	131
2019	4	2015	91
2020	5	2015	68

B. Myeloma Cancer Raw Data

1. By Death Year

Number of Cause-specific Deaths of Myeloma Patients in 1997 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	5	1997	59
1993	4	1997	94
1994	3	1997	124
1995	2	1997	153
1996	1	1997	216
1997	0	1997	244

Number of Cause-specific Deaths of Myeloma Patients in 1998 - 5 Year

Dx. Year	Lifetime	Death Year	N
1993	5	1998	59
1994	4	1998	82
1995	3	1998	108
1996	2	1998	170
1997	1	1998	240
1998	0	1998	238

Number of Cause-specific Deaths of Myeloma Patients in 1999 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1994	5	1999	77
1995	4	1999	84
1996	3	1999	123
1997	2	1999	186
1998	1	1999	246
1999	0	1999	271

Number of Cause-specific Deaths of Myeloma Patients in 2000 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	5	2000	74
1996	4	2000	76
1997	3	2000	141
1998	2	2000	151
1999	1	2000	214
2000	0	2000	260

Number of Cause-specific Deaths of Myeloma Patients in 2001 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	5	2001	74
1997	4	2001	106
1998	3	2001	150
1999	2	2001	177
2000	1	2001	236

2001	0	2001	291

The remaining 5-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Myeloma Patients in 2002 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	10	2002	13
1993	9	2002	14
1994	8	2002	18
1995	7	2002	40
1996	6	2002	44
1997	5	2002	62
1998	4	2002	85
1999	3	2002	157
2000	2	2002	195
2001	1	2002	253
2002	0	2002	250

Number of Cause-specific Deaths of Myeloma Patients in 2003 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1993	10	2003	16
1994	9	2003	16
1995	8	2003	20
1996	7	2003	37
1997	6	2003	53
1998	5	2003	64
1999	4	2003	91
2000	3	2003	122
2001	2	2003	167
2002	1	2003	258
2003	0	2003	270

Number of Cause-specific Deaths of Myeloma Patients in 2004 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1994	10	2004	9

1995	9	2004	15
1996	8	2004	22
1997	7	2004	34
1998	6	2004	59
1999	5	2004	61
2000	4	2004	87
2001	3	2004	99
2002	2	2004	160
2003	1	2004	232
2004	0	2004	279

Number of Cause-specific Deaths of Myeloma Patients in 2005 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	10	2005	15
1996	9	2005	22
1997	8	2005	23
1998	7	2005	27
1999	6	2005	44
2000	5	2005	85
2001	4	2005	88
2002	3	2005	119
2003	2	2005	158
2004	1	2005	217
2005	0	2005	309

Number of Cause-specific Deaths of Myeloma Patients in 2006 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	10	2006	20
1997	9	2006	21
1998	8	2006	20
1999	7	2006	33
2000	6	2006	54
2001	5	2006	74
2002	4	2006	77
2003	3	2006	126

2004	2	2006	144
2005	1	2006	229
2006	0	2006	283

Number of Cause-specific Deaths of Myeloma Patients in 2007 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1997	10	2007	12
1998	9	2007	15
1999	8	2007	27
2000	7	2007	44
2001	6	2007	37
2002	5	2007	76
2003	4	2007	90
2004	3	2007	132
2005	2	2007	147
2006	1	2007	239
2007	0	2007	269

Number of Cause-specific Deaths of Myeloma Patients in 2008 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1998	10	2008	15
1999	9	2008	21
2000	8	2008	27
2001	7	2008	39
2002	6	2008	45
2003	5	2008	79
2004	4	2008	97
2005	3	2008	106
2006	2	2008	125
2007	1	2008	215
2008	0	2008	266

Number of Cause-specific Deaths of Myeloma Patients in 2009 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**

1999	10	2009	11
2000	9	2009	20
2001	8	2009	26
2002	7	2009	36
2003	6	2009	63
2004	5	2009	90
2005	4	2009	79
2006	3	2009	128
2007	2	2009	135
2008	1	2009	211
2009	0	2009	238

Number of Cause-specific Deaths of Myeloma Patients in 2010 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2000	10	2010	8
2001	9	2010	19
2002	8	2010	35
2003	7	2010	52
2004	6	2010	64
2005	5	2010	89
2006	4	2010	81
2007	3	2010	107
2008	2	2010	175
2009	1	2010	241
2010	0	2010	239

Number of Cause-specific Deaths of Myeloma Patients in 2011 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2001	10	2011	20
2002	9	2011	29
2003	8	2011	38
2004	7	2011	50
2005	6	2011	60
2006	5	2011	75
2007	4	2011	110
2008	3	2011	133
2009	2	2011	179
2010	1	2011	257

2011	0	2011	254

The remaining 5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Myeloma Patients in 2012 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	20	2012	1
1993	19	2012	2
1994	18	2012	3
1995	17	2012	2
1996	16	2012	5
1997	15	2012	3
1998	14	2012	10
1999	13	2012	3
2000	12	2012	19
2001	11	2012	16
2002	10	2012	14
2003	9	2012	30
2004	8	2012	34
2005	7	2012	64
2006	6	2012	79
2007	5	2012	86
2008	4	2012	107
2009	3	2012	140
2010	2	2012	188
2011	1	2012	253
2012	0	2012	299

Number of Cause-specific Deaths of Myeloma Patients in 2013 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1993	20	2013	0
1994	19	2013	5
1995	18	2013	4
1996	17	2013	6
1997	16	2013	4
1998	15	2013	5
1999	14	2013	7
2000	13	2013	10
2001	12	2013	16
2002	11	2013	13
2003	10	2013	25

2004	9	2013	25
2005	8	2013	39
2006	7	2013	46
2007	6	2013	62
2008	5	2013	93
2009	4	2013	113
2010	3	2013	137
2011	2	2013	154
2012	1	2013	237
2013	0	2013	272

Number of Cause-specific Deaths of Myeloma Patients in 2014 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1994	20	2014	0
1995	19	2014	5
1996	18	2014	3
1997	17	2014	6
1998	16	2014	11
1999	15	2014	8
2000	14	2014	5
2001	13	2014	13
2002	12	2014	12
2003	11	2014	18
2004	10	2014	23
2005	9	2014	29
2006	8	2014	34
2007	7	2014	53
2008	6	2014	67
2009	5	2014	84
2010	4	2014	104
2011	3	2014	138
2012	2	2014	172
2013	1	2014	253
2014	0	2014	289

Number of Cause-specific Deaths of Myeloma Patients in 2015 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	20	2015	3
1996	19	2015	2

1997	18	2015	3
1998	17	2015	5
1999	16	2015	2
2000	15	2015	9
2001	14	2015	9
2002	13	2015	8
2003	12	2015	14
2004	11	2015	18
2005	10	2015	29
2006	9	2015	32
2007	8	2015	40
2008	7	2015	54
2009	6	2015	77
2010	5	2015	89
2011	4	2015	111
2012	3	2015	106
2013	2	2015	180
2014	1	2015	230
2015	0	2015	291

Number of Cause-specific Deaths of Myeloma Patients in 2016 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	20	2016	4
1997	19	2016	2
1998	18	2016	4
1999	17	2016	3
2000	16	2016	6
2001	15	2016	15
2002	14	2016	10
2003	13	2016	16
2004	12	2016	17
2005	11	2016	28
2006	10	2016	20
2007	9	2016	47
2008	8	2016	37
2009	7	2016	48
2010	6	2016	70
2011	5	2016	104
2012	4	2016	100
2013	3	2016	111
2014	2	2016	148

2015	1	2016	239
2016	0	2016	289

Number of Cause-specific Deaths of Myeloma Patients in 2017 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1997	20	2017	1
1998	19	2017	7
1999	18	2017	5
2000	17	2017	4
2001	16	2017	7
2002	15	2017	8
2003	14	2017	10
2004	13	2017	13
2005	12	2017	22
2006	11	2017	20
2007	10	2017	22
2008	9	2017	38
2009	8	2017	56
2010	7	2017	60
2011	6	2017	79
2012	5	2017	81
2013	4	2017	117
2014	3	2017	131
2015	2	2017	149
2016	1	2017	232
2017	0	2017	271

Number of Cause-specific Deaths of Myeloma Patients in 2018 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1998	20	2018	2
1999	19	2018	3
2000	18	2018	5
2001	17	2018	5
2002	16	2018	7
2003	15	2018	12
2004	14	2018	14
2005	13	2018	16
2006	12	2018	14
2007	11	2018	27
2008	10	2018	32

2009	9	2018	33
2010	8	2018	61
2011	7	2018	55
2012	6	2018	59
2013	5	2018	88
2014	4	2018	103
2015	3	2018	118
2016	2	2018	167
2017	1	2018	218
2018	0	2018	278

Number of Cause-specific Deaths of Myeloma Patients in 2019 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1999	20	2019	3
2000	19	2019	2
2001	18	2019	3
2002	17	2019	6
2003	16	2019	11
2004	15	2019	12
2005	14	2019	13
2006	13	2019	16
2007	12	2019	15
2008	11	2019	36
2009	10	2019	30
2010	9	2019	47
2011	8	2019	46
2012	7	2019	73
2013	6	2019	69
2014	5	2019	90
2015	4	2019	101
2016	3	2019	118
2017	2	2019	147
2018	1	2019	213
2019	0	2019	285

Number of Cause-specific Deaths of Myeloma Patients in 2020 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2000	20	2020	1
2001	19	2020	2
2002	18	2020	4

2003	17	2020	6
2004	16	2020	10
2005	15	2020	9
2006	14	2020	9
2007	13	2020	15
2008	12	2020	17
2009	11	2020	24
2010	10	2020	36
2011	9	2020	40
2012	8	2020	49
2013	7	2020	77
2014	6	2020	74
2015	5	2020	89
2016	4	2020	105
2017	3	2020	129
2018	2	2020	146
2019	1	2020	237
2020	0	2020	271

2. By Diagnosis Year

5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1992 - 20 Year			
Death Yr.	Lifetime	Dx. Year	N
1992	0	1992	252
1993	1	1992	228
1994	2	1992	161
1995	3	1992	115
1996	4	1992	76
1997	5	1992	59
1998	6	1992	33
1999	7	1992	30
2000	8	1992	23
2001	9	1992	21
2002	10	1992	13
2003	11	1992	8

2004	12	1992	5
2005	13	1992	5
2006	14	1992	2
2007	15	1992	2
2008	16	1992	6
2009	17	1992	1
2010	18	1992	1
2011	19	1992	1
2012	20	1992	1

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1993 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1993	0	1993	223
1994	1	1993	215
1995	2	1993	166
1996	3	1993	130
1997	4	1993	94
1998	5	1993	59
1999	6	1993	42
2000	7	1993	42
2001	8	1993	17
2002	9	1993	14
2003	10	1993	16
2004	11	1993	8
2005	12	1993	9
2006	13	1993	8
2007	14	1993	7
2008	15	1993	3
2009	16	1993	2
2010	17	1993	2
2011	18	1993	2
2012	19	1993	2
2013	20	1993	0

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1994 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**

1994	0	1994	250
1995	1	1994	223
1996	2	1994	174
1997	3	1994	124
1998	4	1994	82
1999	5	1994	77
2000	6	1994	46
2001	7	1994	34
2002	8	1994	18
2003	9	1994	16
2004	10	1994	9
2005	11	1994	13
2006	12	1994	4
2007	13	1994	5
2008	14	1994	6
2009	15	1994	6
2010	16	1994	6
2011	17	1994	1
2012	18	1994	3
2013	19	1994	5
2014	20	1994	0

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1995 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1995	0	1995	235
1996	1	1995	240
1997	2	1995	153
1998	3	1995	108
1999	4	1995	84
2000	5	1995	74
2001	6	1995	38
2002	7	1995	40
2003	8	1995	20
2004	9	1995	15
2005	10	1995	15
2006	11	1995	14
2007	12	1995	8
2008	13	1995	5
2009	14	1995	5

2010	15	1995	10
2011	16	1995	3
2012	17	1995	2
2013	18	1995	4
2014	19	1995	5
2015	20	1995	3

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1996 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1996	0	1996	257
1997	1	1996	216
1998	2	1996	170
1999	3	1996	123
2000	4	1996	76
2001	5	1996	74
2002	6	1996	44
2003	7	1996	37
2004	8	1996	22
2005	9	1996	22
2006	10	1996	20
2007	11	1996	16
2008	12	1996	9
2009	13	1996	16
2010	14	1996	9
2011	15	1996	2
2012	16	1996	5
2013	17	1996	6
2014	18	1996	3
2015	19	1996	2
2016	20	1996	4

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1997 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1997	0	1997	244
1998	1	1997	240
1999	2	1997	186
2000	3	1997	141

2001	4	1997	106
2002	5	1997	62
2003	6	1997	53
2004	7	1997	34
2005	8	1997	23
2006	9	1997	21
2007	10	1997	12
2008	11	1997	17
2009	12	1997	8
2010	13	1997	8
2011	14	1997	4
2012	15	1997	3
2013	16	1997	4
2014	17	1997	6
2015	18	1997	3
2016	19	1997	2
2017	20	1997	1

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1998 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1998	0	1998	238
1999	1	1998	246
2000	2	1998	151
2001	3	1998	150
2002	4	1998	85
2003	5	1998	64
2004	6	1998	59
2005	7	1998	27
2006	8	1998	20
2007	9	1998	15
2008	10	1998	15
2009	11	1998	15
2010	12	1998	15
2011	13	1998	4
2012	14	1998	10
2013	15	1998	5
2014	16	1998	11
2015	17	1998	5
2016	18	1998	4

2017	19	1998	7
2018	20	1998	2

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 1999 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1999	0	1999	271
2000	1	1999	214
2001	2	1999	177
2002	3	1999	157
2003	4	1999	91
2004	5	1999	61
2005	6	1999	44
2006	7	1999	33
2007	8	1999	27
2008	9	1999	21
2009	10	1999	11
2010	11	1999	10
2011	12	1999	6
2012	13	1999	3
2013	14	1999	7
2014	15	1999	8
2015	16	1999	2
2016	17	1999	3
2017	18	1999	5
2018	19	1999	3
2019	20	1999	3

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2000 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2000	0	2000	260
2001	1	2000	236
2002	2	2000	195
2003	3	2000	122
2004	4	2000	87
2005	5	2000	85
2006	6	2000	54
2007	7	2000	44

2008	8	2000	27
2009	9	2000	20
2010	10	2000	8
2011	11	2000	19
2012	12	2000	19
2013	13	2000	10
2014	14	2000	5
2015	15	2000	9
2016	16	2000	6
2017	17	2000	4
2018	18	2000	5
2019	19	2000	2
2020	20	2000	1

5-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2001 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2001	0	2001	291
2002	1	2001	253
2003	2	2001	167
2004	3	2001	99
2005	4	2001	88
2006	5	2001	74
2007	6	2001	37
2008	7	2001	39
2009	8	2001	26
2010	9	2001	19
2011	10	2001	20

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2002 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2002	0	2002	250
2003	1	2002	258
2004	2	2002	160
2005	3	2002	119
2006	4	2002	77
2007	5	2002	76

2008	6	2002	45
2009	7	2002	36
2010	8	2002	35
2011	9	2002	29
2012	10	2002	14

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2003 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2003	0	2003	270
2004	1	2003	232
2005	2	2003	158
2006	3	2003	126
2007	4	2003	90
2008	5	2003	79
2009	6	2003	63
2010	7	2003	52
2011	8	2003	38
2012	9	2003	30
2013	10	2003	25

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2004 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2004	0	2004	279
2005	1	2004	217
2006	2	2004	144
2007	3	2004	132
2008	4	2004	97
2009	5	2004	90
2010	6	2004	64
2011	7	2004	50
2012	8	2004	34
2013	9	2004	25
2014	10	2004	23

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2005 - 10 Year

Death Yr.	Lifetime	Dx. Year	N
2005	0	2005	309
2006	1	2005	229
2007	2	2005	147
2008	3	2005	106
2009	4	2005	79
2010	5	2005	89
2011	6	2005	60
2012	7	2005	64
2013	8	2005	39
2014	9	2005	29
2015	10	2005	29

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2006 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2006	0	2006	283
2007	1	2006	239
2008	2	2006	125
2009	3	2006	128
2010	4	2006	81
2011	5	2006	75
2012	6	2006	79
2013	7	2006	46
2014	8	2006	34
2015	9	2006	32
2016	10	2006	20

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2007 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2007	0	2007	269
2008	1	2007	215
2009	2	2007	135
2010	3	2007	107
2011	4	2007	110
2012	5	2007	86
2013	6	2007	62

2014	7	2007	53
2015	8	2007	40
2016	9	2007	47
2017	10	2007	22

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2008 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2008	0	2008	266
2009	1	2008	211
2010	2	2008	175
2011	3	2008	133
2012	4	2008	107
2013	5	2008	93
2014	6	2008	67
2015	7	2008	54
2016	8	2008	37
2017	9	2008	38
2018	10	2008	32

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2009 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2009	0	2009	238
2010	1	2009	241
2011	2	2009	179
2012	3	2009	140
2013	4	2009	113
2014	5	2009	84
2015	6	2009	77
2016	7	2009	48
2017	8	2009	56
2018	9	2009	33
2019	10	2009	30

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2010 - 10 Year

Death Yr.	Lifetime	Dx. Year	N
2010	0	2010	239
2011	1	2010	257
2012	2	2010	188
2013	3	2010	137
2014	4	2010	104
2015	5	2010	89
2016	6	2010	70
2017	7	2010	60
2018	8	2010	61
2019	9	2010	47
2020	10	2010	36

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2011 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2011	0	2011	254
2012	1	2011	253
2013	2	2011	154
2014	3	2011	138
2015	4	2011	111
2016	5	2011	104

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2012 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2012	0	2012	299
2013	1	2012	237
2014	2	2012	172
2015	3	2012	106
2016	4	2012	100
2017	5	2012	81

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2013 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**

2013	0	2013	272
2014	1	2013	253
2015	2	2013	180
2016	3	2013	111
2017	4	2013	117
2018	5	2013	88

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2014 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2014	0	2014	289
2015	1	2014	230
2016	2	2014	148
2017	3	2014	131
2018	4	2014	103
2019	5	2014	90

Number of Cause-specific Deaths Based on Diagnoses of Myeloma Patients in 2015 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2015	0	2015	291
2016	1	2015	239
2017	2	2015	149
2018	3	2015	118
2019	4	2015	101
2020	5	2015	89

C. Lung and Bronchus Cancer Raw Data

1. By Death Year

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 1997 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	5	1997	169
1993	4	1997	251
1994	3	1997	519

1995	2	1997	1,413
1996	1	1997	4,722
1997	0	1997	6,518

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 1998 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1993	5	1998	161
1994	4	1998	293
1995	3	1998	525
1996	2	1998	1,366
1997	1	1998	4,802
1998	0	1998	6,434

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 1999 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1994	5	1999	167
1995	4	1999	299
1996	3	1999	598
1997	2	1999	1,391
1998	1	1999	4,828
1999	0	1999	6,462

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2000 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	5	2000	188
1996	4	2000	306
1997	3	2000	561
1998	2	2000	1,521
1999	1	2000	4,823
2000	0	2000	6,477

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2001 - 5 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	5	2001	183
1997	4	2001	310
1998	3	2001	585
1999	2	2001	1,463
2000	1	2001	4,615
2001	0	2001	6,520

The remaining 5-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2002 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	10	2002	45
1993	9	2002	67
1994	8	2002	61
1995	7	2002	78
1996	6	2002	123
1997	5	2002	175
1998	4	2002	345
1999	3	2002	584
2000	2	2002	1,432
2001	1	2002	4,594
2002	0	2002	6,528

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2003 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1993	10	2003	57
1994	9	2003	50
1995	8	2003	74
1996	7	2003	123
1997	6	2003	123

1998	5	2003	232
1999	4	2003	330
2000	3	2003	594
2001	2	2003	1,418
2002	1	2003	4,728
2003	0	2003	6,448

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2004 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1994	10	2004	39
1995	9	2004	72
1996	8	2004	78
1997	7	2004	94
1998	6	2004	149
1999	5	2004	189
2000	4	2004	330
2001	3	2004	630
2002	2	2004	1,402
2003	1	2004	4,708
2004	0	2004	6,443

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2005 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	10	2005	49
1996	9	2005	65
1997	8	2005	100
1998	7	2005	104
1999	6	2005	175
2000	5	2005	212
2001	4	2005	324
2002	3	2005	634
2003	2	2005	1,498
2004	1	2005	4,546
2005	0	2005	6,526

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2006 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	10	2006	60
1997	9	2006	56
1998	8	2006	80
1999	7	2006	108
2000	6	2006	150
2001	5	2006	209
2002	4	2006	334
2003	3	2006	670
2004	2	2006	1,401
2005	1	2006	4,593
2006	0	2006	6,275

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2007 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1997	10	2007	52
1998	9	2007	58
1999	8	2007	80
2000	7	2007	110
2001	6	2007	146
2002	5	2007	229
2003	4	2007	387
2004	3	2007	685
2005	2	2007	1,462
2006	1	2007	4,554
2007	0	2007	6,390

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2008 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1998	10	2008	49
1999	9	2008	74
2000	8	2008	82
2001	7	2008	103
2002	6	2008	159

2003	5	2008	232
2004	4	2008	374
2005	3	2008	663
2006	2	2008	1,484
2007	1	2008	4,449
2008	0	2008	6,085

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2009 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1999	10	2009	51
2000	9	2009	58
2001	8	2009	93
2002	7	2009	103
2003	6	2009	179
2004	5	2009	250
2005	4	2009	399
2006	3	2009	700
2007	2	2009	1,516
2008	1	2009	4,390
2009	0	2009	6,218

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2010 - 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2000	10	2010	53
2001	9	2010	53
2002	8	2010	99
2003	7	2010	123
2004	6	2010	190
2005	5	2010	252
2006	4	2010	408
2007	3	2010	708
2008	2	2010	1,560
2009	1	2010	4,533
2010	0	2010	6,112

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2011- 10 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2001	10	2011	59
2002	9	2011	75
2003	8	2011	111
2004	7	2011	135
2005	6	2011	169
2006	5	2011	254
2007	4	2011	414
2008	3	2011	755
2009	2	2011	1,608
2010	1	2011	4,245
2011	0	2011	5,859

The remaining 5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2012 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1992	20	2012	8
1993	19	2012	13
1994	18	2012	9
1995	17	2012	16
1996	16	2012	8
1997	15	2012	28
1998	14	2012	27
1999	13	2012	44
2000	12	2012	43
2001	11	2012	52
2002	10	2012	56
2003	9	2012	73
2004	8	2012	97
2005	7	2012	116
2006	6	2012	147
2007	5	2012	264
2008	4	2012	434

2009	3	2012	778
2010	2	2012	1,483
2011	1	2012	4,215
2012	0	2012	5,909

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2013 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1993	20	2013	9
1994	19	2013	17
1995	18	2013	18
1996	17	2013	17
1997	16	2013	20
1998	15	2013	28
1999	14	2013	29
2000	13	2013	34
2001	12	2013	44
2002	11	2013	51
2003	10	2013	52
2004	9	2013	71
2005	8	2013	110
2006	7	2013	115
2007	6	2013	195
2008	5	2013	263
2009	4	2013	415
2010	3	2013	726
2011	2	2013	1,493
2012	1	2013	4,310
2013	0	2013	5,875

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2014 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1994	20	2014	4
1995	19	2014	17
1996	18	2014	14
1997	17	2014	10
1998	16	2014	13
1999	15	2014	14
2000	14	2014	31

2001	13	2014	36
2002	12	2014	35
2003	11	2014	51
2004	10	2014	72
2005	9	2014	83
2006	8	2014	114
2007	7	2014	139
2008	6	2014	191
2009	5	2014	263
2010	4	2014	414
2011	3	2014	756
2012	2	2014	1,548
2013	1	2014	4,087
2014	0	2014	5,726

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2015 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1995	20	2015	9
1996	19	2015	11
1997	18	2015	14
1998	17	2015	22
1999	16	2015	22
2000	15	2015	35
2001	14	2015	33
2002	13	2015	21
2003	12	2015	39
2004	11	2015	57
2005	10	2015	61
2006	9	2015	97
2007	8	2015	108
2008	7	2015	169
2009	6	2015	190
2010	5	2015	313
2011	4	2015	435
2012	3	2015	735
2013	2	2015	1,543
2014	1	2015	4,191
2015	0	2015	5,822

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2016 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1996	20	2016	11
1997	19	2016	11
1998	18	2016	11
1999	17	2016	26
2000	16	2016	21
2001	15	2016	28
2002	14	2016	25
2003	13	2016	43
2004	12	2016	40
2005	11	2016	51
2006	10	2016	49
2007	9	2016	86
2008	8	2016	111
2009	7	2016	152
2010	6	2016	175
2011	5	2016	261
2012	4	2016	430
2013	3	2016	712
2014	2	2016	1,487
2015	1	2016	3,948
2016	0	2016	5,602

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2017 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1997	20	2017	10
1998	19	2017	8
1999	18	2017	17
2000	17	2017	20
2001	16	2017	15
2002	15	2017	20
2003	14	2017	26
2004	13	2017	49
2005	12	2017	44
2006	11	2017	63
2007	10	2017	79
2008	9	2017	87

2009	8	2017	133
2010	7	2017	147
2011	6	2017	201
2012	5	2017	276
2013	4	2017	414
2014	3	2017	720
2015	2	2017	1,429
2016	1	2017	3,842
2017	0	2017	5,321

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2018 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1998	20	2018	9
1999	19	2018	19
2000	18	2018	14
2001	17	2018	14
2002	16	2018	19
2003	15	2018	27
2004	14	2018	32
2005	13	2018	41
2006	12	2018	39
2007	11	2018	55
2008	10	2018	79
2009	9	2018	102
2010	8	2018	101
2011	7	2018	145
2012	6	2018	194
2013	5	2018	292
2014	4	2018	450
2015	3	2018	784
2016	2	2018	1,411
2017	1	2018	3,673
2018	0	2018	5,117

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2019 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
1999	20	2019	9
2000	19	2019	11

2001	18	2019	15
2002	17	2019	22
2003	16	2019	16
2004	15	2019	18
2005	14	2019	42
2006	13	2019	38
2007	12	2019	41
2008	11	2019	55
2009	10	2019	67
2010	9	2019	101
2011	8	2019	121
2012	7	2019	150
2013	6	2019	200
2014	5	2019	297
2015	4	2019	472
2016	3	2019	751
2017	2	2019	1,451
2018	1	2019	3,470
2019	0	2019	4,908

Number of Cause-specific Deaths of Lung and Bronchus Cancer Patients in 2020 - 20 Year			
Dx. Year	**Lifetime**	**Death Year**	**N**
2000	20	2020	9
2001	19	2020	18
2002	18	2020	16
2003	17	2020	18
2004	16	2020	16
2005	15	2020	17
2006	14	2020	38
2007	13	2020	44
2008	12	2020	43
2009	11	2020	67
2010	10	2020	79
2011	9	2020	100
2012	8	2020	115
2013	7	2020	160
2014	6	2020	217
2015	5	2020	314
2016	4	2020	468
2017	3	2020	778

2018	2	2020	1,329
2019	1	2020	3,325
2020	0	2020	4,567

2. By Diagnosis Year

5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 1992 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1992	0	1992	6,219
1993	1	1992	4,930
1994	2	1992	1,474
1995	3	1992	529
1996	4	1992	288
1997	5	1992	169
1998	6	1992	128
1999	7	1992	95
2000	8	1992	80
2001	9	1992	52
2002	10	1992	45
2003	11	1992	56
2004	12	1992	33
2005	13	1992	30
2006	14	1992	18
2007	15	1992	21
2008	16	1992	12
2009	17	1992	16
2010	18	1992	24
2011	19	1992	10
2012	20	1992	8

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 1993 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1993	0	1993	6,194
1994	1	1993	4,877
1995	2	1993	1,390

1996	3	1993	544
1997	4	1993	251
1998	5	1993	161
1999	6	1993	131
2000	7	1993	81
2001	8	1993	73
2002	9	1993	67
2003	10	1993	57
2004	11	1993	50
2005	12	1993	32
2006	13	1993	27
2007	14	1993	24
2008	15	1993	23
2009	16	1993	22
2010	17	1993	9
2011	18	1993	13
2012	19	1993	13
2013	20	1993	9

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 1994 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1994	0	1994	6,201
1995	1	1994	4,769
1996	2	1994	1,331
1997	3	1994	519
1998	4	1994	293
1999	5	1994	167
2000	6	1994	134
2001	7	1994	93
2002	8	1994	61
2003	9	1994	50
2004	10	1994	39
2005	11	1994	43
2006	12	1994	44
2007	13	1994	34
2008	14	1994	25
2009	15	1994	18
2010	16	1994	21
2011	17	1994	16
2012	18	1994	9

2013	19	1994	17
2014	20	1994	4

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 1995 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1995	0	1995	6,498
1996	1	1995	4,713
1997	2	1995	1,413
1998	3	1995	525
1999	4	1995	299
2000	5	1995	188
2001	6	1995	129
2002	7	1995	78
2003	8	1995	74
2004	9	1995	72
2005	10	1995	49
2006	11	1995	34
2007	12	1995	45
2008	13	1995	48
2009	14	1995	29
2010	15	1995	18
2011	16	1995	19
2012	17	1995	16
2013	18	1995	18
2014	19	1995	17
2015	20	1995	9

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 1996 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1996	0	1996	6,496
1997	1	1996	4,722
1998	2	1996	1,366
1999	3	1996	598
2000	4	1996	306
2001	5	1996	183
2002	6	1996	123
2003	7	1996	123

2004	8	1996	78
2005	9	1996	65
2006	10	1996	60
2007	11	1996	56
2008	12	1996	32
2009	13	1996	26
2010	14	1996	28
2011	15	1996	33
2012	16	1996	8
2013	17	1996	17
2014	18	1996	14
2015	19	1996	11
2016	20	1996	11

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 1997 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1997	0	1997	6,518
1998	1	1997	4,802
1999	2	1997	1,391
2000	3	1997	561
2001	4	1997	310
2002	5	1997	175
2003	6	1997	123
2004	7	1997	94
2005	8	1997	100
2006	9	1997	56
2007	10	1997	52
2008	11	1997	48
2009	12	1997	26
2010	13	1997	35
2011	14	1997	31
2012	15	1997	28
2013	16	1997	20
2014	17	1997	10
2015	18	1997	14
2016	19	1997	11
2017	20	1997	10

Number of Cause-specific Deaths Based on Diagnoses of Lung and

Bronchus Cancer Patients in 1998 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1998	0	1998	6,434
1999	1	1998	4,828
2000	2	1998	1,521
2001	3	1998	585
2002	4	1998	345
2003	5	1998	232
2004	6	1998	149
2005	7	1998	104
2006	8	1998	80
2007	9	1998	58
2008	10	1998	49
2009	11	1998	40
2010	12	1998	38
2011	13	1998	31
2012	14	1998	27
2013	15	1998	28
2014	16	1998	13
2015	17	1998	22
2016	18	1998	11
2017	19	1998	8
2018	20	1998	9

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 1999 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
1999	0	1999	6,462
2000	1	1999	4,823
2001	2	1999	1,463
2002	3	1999	584
2003	4	1999	330
2004	5	1999	189
2005	6	1999	175
2006	7	1999	108
2007	8	1999	80
2008	9	1999	74
2009	10	1999	51
2010	11	1999	55

2011	12	1999	41
2012	13	1999	44
2013	14	1999	29
2014	15	1999	14
2015	16	1999	22
2016	17	1999	26
2017	18	1999	17
2018	19	1999	19
2019	20	1999	9

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2000 - 20 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2000	0	2000	6,477
2001	1	2000	4,615
2002	2	2000	1,432
2003	3	2000	594
2004	4	2000	330
2005	5	2000	212
2006	6	2000	150
2007	7	2000	110
2008	8	2000	82
2009	9	2000	58
2010	10	2000	53
2011	11	2000	37
2012	12	2000	43
2013	13	2000	34
2014	14	2000	31
2015	15	2000	35
2016	16	2000	21
2017	17	2000	20
2018	18	2000	14
2019	19	2000	11
2020	20	2000	9

5-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2001 - 10 Year

Death Yr.	Lifetime	Dx. Year	N
2001	0	2001	6,520
2002	1	2001	4,594
2003	2	2001	1,418
2004	3	2001	630
2005	4	2001	324
2006	5	2001	209
2007	6	2001	146
2008	7	2001	103
2009	8	2001	93
2010	9	2001	53
2011	10	2001	59

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2002 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2002	0	2002	6,528
2003	1	2002	4,728
2004	2	2002	1,402
2005	3	2002	634
2006	4	2002	334
2007	5	2002	229
2008	6	2002	159
2009	7	2002	103
2010	8	2002	99
2011	9	2002	75
2012	10	2002	56

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2003 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2003	0	2003	6,448
2004	1	2003	4,708
2005	2	2003	1,498
2006	3	2003	670
2007	4	2003	387
2008	5	2003	232

2009	6	2003	179
2010	7	2003	123
2011	8	2003	111
2012	9	2003	73
2013	10	2003	52

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2004 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2004	0	2004	6,443
2005	1	2004	4,546
2006	2	2004	1,401
2007	3	2004	685
2008	4	2004	374
2009	5	2004	250
2010	6	2004	190
2011	7	2004	135
2012	8	2004	97
2013	9	2004	71
2014	10	2004	72

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2005 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2005	0	2005	6,526
2006	1	2005	4,593
2007	2	2005	1,462
2008	3	2005	663
2009	4	2005	399
2010	5	2005	252
2011	6	2005	169
2012	7	2005	116
2013	8	2005	110
2014	9	2005	83
2015	10	2005	61

Number of Cause-specific Deaths Based on Diagnoses of Lung and

Bronchus Cancer Patients in 2006 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2006	0	2006	6,275
2007	1	2006	4,554
2008	2	2006	1,484
2009	3	2006	700
2010	4	2006	408
2011	5	2006	254
2012	6	2006	147
2013	7	2006	115
2014	8	2006	114
2015	9	2006	97
2016	10	2006	49

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2007 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2007	0	2007	6,390
2008	1	2007	4,449
2009	2	2007	1,516
2010	3	2007	708
2011	4	2007	414
2012	5	2007	264
2013	6	2007	195
2014	7	2007	139
2015	8	2007	108
2016	9	2007	86
2017	10	2007	79

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2008 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2008	0	2008	6,085
2009	1	2008	4,390
2010	2	2008	1,560
2011	3	2008	755
2012	4	2008	434

2013	5	2008	263
2014	6	2008	191
2015	7	2008	169
2016	8	2008	111
2017	9	2008	87
2018	10	2008	79

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2009 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2009	0	2009	6,218
2010	1	2009	4,533
2011	2	2009	1,608
2012	3	2009	778
2013	4	2009	415
2014	5	2009	263
2015	6	2009	190
2016	7	2009	152
2017	8	2009	133
2018	9	2009	102
2019	10	2009	67

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2010 - 10 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2010	0	2010	6,112
2011	1	2010	4,245
2012	2	2010	1,483
2013	3	2010	726
2014	4	2010	414
2015	5	2010	313
2016	6	2010	175
2017	7	2010	147
2018	8	2010	101
2019	9	2010	101
2020	10	2010	79

Number of Cause-specific Deaths Based on Diagnoses of Lung and

Bronchus Cancer Patients in 2011 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2011	0	2011	5,859
2012	1	2011	4,215
2013	2	2011	1,493
2014	3	2011	756
2015	4	2011	435
2016	5	2011	261

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2012 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2012	0	2012	5,909
2013	1	2012	4,310
2014	2	2012	1,548
2015	3	2012	735
2016	4	2012	430
2017	5	2012	276

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2013 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2013	0	2013	5,875
2014	1	2013	4,087
2015	2	2013	1,543
2016	3	2013	712
2017	4	2013	414
2018	5	2013	292

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2014 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2014	0	2014	5,726
2015	1	2014	4,191

2016	2	2014	1,487
2017	3	2014	720
2018	4	2014	450
2019	5	2014	297

Number of Cause-specific Deaths Based on Diagnoses of Lung and Bronchus Cancer Patients in 2015 - 5 Year			
Death Yr.	**Lifetime**	**Dx. Year**	**N**
2015	0	2015	5,822
2016	1	2015	3,948
2017	2	2015	1,429
2018	3	2015	784
2019	4	2015	472
2020	5	2015	314

E. Prostate Cancer Raw Data

1. By Death Year

Number of Cause-specific Deaths of Prostate Cancer Patients in 1997 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1992	5	1997	380
1992	4	1997	348
1992	3	1997	367
1992	2	1997	403
1992	1	1997	396
1992	0	1997	291

Number of Cause-specific Deaths of Prostate Cancer Patients in 1998 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1993	5	1998	323
1994	4	1998	281
1995	3	1998	306
1996	2	1998	390
1997	1	1998	356
1998	0	1998	307

Number of Cause-specific Deaths of Prostate Cancer Patients in 1999 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1994	5	1999	290
1995	4	1999	282
1996	3	1999	303
1997	2	1999	358
1998	1	1999	387
1999	0	1999	302

Number of Cause-specific Deaths of Prostate Cancer Patients in 2000 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1995	5	2000	219
1996	4	2000	257
1997	3	2000	288
1998	2	2000	309
1999	1	2000	371
2000	0	2000	308

Number of Cause-specific Deaths of Prostate Cancer Patients in 2001 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1996	5	2001	236
1997	4	2001	240
1998	3	2001	254
1999	2	2001	320
2000	1	2001	358
2001	0	2001	312

The remaining 5-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Prostate Cancer Patients in 2002 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1992	10	2002	277
1993	9	2002	263

1994	8	2002	199
1995	7	2002	219
1996	6	2002	221
1997	5	2002	266
1998	4	2002	260
1999	3	2002	291
2000	2	2002	351
2001	1	2002	323
2002	0	2002	325

Number of Cause-specific Deaths of Prostate Cancer Patients in 2003 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1993	10	2003	224
1994	9	2003	199
1995	8	2003	196
1996	7	2003	187
1997	6	2003	237
1998	5	2003	230
1999	4	2003	267
2000	3	2003	305
2001	2	2003	295
2002	1	2003	364
2003	0	2003	282

Number of Cause-specific Deaths of Prostate Cancer Patients in 2004 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1994	10	2004	195
1995	9	2004	163
1996	8	2004	200
1997	7	2004	194
1998	6	2004	199
1999	5	2004	228
2000	4	2004	228
2001	3	2004	263
2002	2	2004	278
2003	1	2004	345
2004	0	2004	267

Number of Cause-specific Deaths of Prostate Cancer Patients in 2005 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1995	10	2005	187
1996	9	2005	165
1998	8	2005	167
1999	7	2005	215
2000	6	2005	213
2001	5	2005	245
2002	4	2005	238
2003	3	2005	283
2004	2	2005	316
2005	1	2005	365
2006	0	2005	347

Number of Cause-specific Deaths of Prostate Cancer Patients in 2006 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1996	10	2006	166
1997	9	2006	173
1998	8	2006	197
1999	7	2006	223
2000	6	2006	202
2001	5	2006	193
2002	4	2006	200
2003	3	2006	231
2004	2	2006	279
2005	1	2006	337
2006	0	2006	342

Number of Cause-specific Deaths of Prostate Cancer Patients in 2007 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1997	10	2007	152
1998	9	2007	185
1999	8	2007	185
2000	7	2007	202

2001	6	2007	193
2002	5	2007	200
2003	4	2007	234
2004	3	2007	244
2005	2	2007	323
2006	1	2007	353
2007	0	2007	341

Number of Cause-specific Deaths of Prostate Cancer Patients in 2008 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1998	10	2008	162
1999	9	2008	177
2000	8	2008	175
2001	7	2008	202
2002	6	2008	174
2003	5	2008	217
2004	4	2008	216
2005	3	2008	251
2006	2	2008	326
2007	1	2008	321
2008	0	2008	287

Number of Cause-specific Deaths of Prostate Cancer Patients in 2009 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1999	10	2009	164
2000	9	2009	164
2001	8	2009	167
2002	7	2009	168
2003	6	2009	182
2004	5	2009	174
2005	4	2009	216
2006	3	2009	256
2007	2	2009	270
2008	1	2009	325
2009	0	2009	321

Number of Cause-specific Deaths of Prostate Cancer Patients in 2010 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
2000	10	2010	173
2001	9	2010	177
2002	8	2010	164
2003	7	2010	182
2004	6	2010	202
2005	5	2010	190
2006	4	2010	216
2007	3	2010	235
2008	2	2010	317
2009	1	2010	392
2010	0	2010	290

Number of Cause-specific Deaths of Prostate Cancer Patients in 2011 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
2001	10	2011	157
2002	9	2011	139
2003	8	2011	159
2004	7	2011	171
2005	6	2011	170
2006	5	2011	181
2007	4	2011	226
2008	3	2011	255
2009	2	2011	277
2010	1	2011	359
2011	0	2011	301

The remaining 5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Prostate Cancer Patients in 2012 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1992	20	2012	92
1993	19	2012	82
1994	18	2012	91

1995	17	2012	96
1996	16	2012	91
1997	15	2012	109
1998	14	2012	112
1999	13	2012	120
2000	12	2012	134
2001	11	2012	122
2002	10	2012	153
2003	9	2012	147
2004	8	2012	139
2005	7	2012	156
2006	6	2012	171
2007	5	2012	204
2008	4	2012	192
2009	3	2012	258
2010	2	2012	271
2011	1	2012	370
2012	0	2012	304

Number of Cause-specific Deaths of Prostate Cancer Patients in 2013 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1993	20	2013	80
1994	19	2013	62
1995	18	2013	78
1996	17	2013	89
1997	16	2013	85
1998	15	2013	103
1999	14	2013	134
2000	13	2013	128
2001	12	2013	119
2002	11	2013	151
2003	10	2013	147
2004	9	2013	159
2005	8	2013	154
2006	7	2013	149
2007	6	2013	175
2008	5	2013	193
2009	4	2013	206
2010	3	2013	238
2011	2	2013	292
2012	1	2013	355

2013	0	2013	332

Number of Cause-specific Deaths of Prostate Cancer Patients in 2014 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1994	20	2014	67
1995	19	2014	90
1996	18	2014	80
1997	17	2014	100
1998	16	2014	109
1999	15	2014	115
2000	14	2014	120
2001	13	2014	127
2002	12	2014	125
2003	11	2014	132
2004	10	2014	133
2005	9	2014	137
2006	8	2014	157
2007	7	2014	155
2008	6	2014	168
2009	5	2014	172
2010	4	2014	214
2011	3	2014	239
2012	2	2014	268
2013	1	2014	400
2014	0	2014	387

Number of Cause-specific Deaths of Prostate Cancer Patients in 2015 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1995	20	2015	78
1996	19	2015	75
1997	18	2015	93
1998	17	2015	92
1999	16	2015	128
2000	15	2015	128
2001	14	2015	144
2002	13	2015	140
2003	12	2015	130
2004	11	2015	138

2005	10	2015	130
2006	9	2015	154
2007	8	2015	180
2008	7	2015	150
2009	6	2015	192
2010	5	2015	172
2011	4	2015	192
2012	3	2015	212
2013	2	2015	308
2014	1	2015	369
2015	0	2015	379

Number of Cause-specific Deaths of Prostate Cancer Patients in 2016 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1996	20	2016	78
1997	19	2016	85
1998	18	2016	87
1999	17	2016	109
2000	16	2016	104
2001	15	2016	111
2002	14	2016	152
2003	13	2016	137
2004	12	2016	123
2005	11	2016	142
2006	10	2016	157
2007	9	2016	187
2008	8	2016	136
2009	7	2016	156
2010	6	2016	169
2011	5	2016	195
2012	4	2016	194
2013	3	2016	301
2014	2	2016	347
2015	1	2016	446
2016	0	2016	360

Number of Cause-specific Deaths of Prostate Cancer Patients in 2017 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**

1997	20	2017	90
1998	19	2017	85
1999	18	2017	97
2000	17	2017	119
2001	16	2017	124
2002	15	2017	107
2003	14	2017	113
2004	13	2017	134
2005	12	2017	127
2006	11	2017	163
2007	10	2017	136
2008	9	2017	136
2009	8	2017	164
2010	7	2017	183
2011	6	2017	181
2012	5	2017	180
2013	4	2017	201
2014	3	2017	244
2015	2	2017	336
2016	1	2017	437
2017	0	2017	394

Number of Cause-specific Deaths of Prostate Cancer Patients in 2018 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1998	20	2018	86
1999	19	2018	112
2000	18	2018	99
2001	17	2018	109
2002	16	2018	122
2003	15	2018	115
2004	14	2018	131
2005	13	2018	105
2006	12	2018	145
2007	11	2018	155
2008	10	2018	159
2009	9	2018	175
2010	8	2018	163
2011	7	2018	174
2012	6	2018	169
2013	5	2018	179

2014	4	2018	228
2015	3	2018	338
2016	2	2018	400
2017	1	2018	460
2018	0	2018	419

Number of Cause-specific Deaths of Prostate Cancer Patients in 2019 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1999	20	2019	69
2000	19	2019	85
2001	18	2019	91
2002	17	2019	99
2003	16	2019	112
2004	15	2019	113
2005	14	2019	111
2006	13	2019	134
2007	12	2019	144
2008	11	2019	135
2009	10	2019	151
2010	9	2019	131
2011	8	2019	135
2012	7	2019	163
2013	6	2019	178
2014	5	2019	177
2015	4	2019	233
2016	3	2019	317
2017	2	2019	396
2018	1	2019	472
2019	0	2019	440

Number of Cause-specific Deaths of Prostate Cancer Patients in 2020 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
2000	20	2020	64
2001	19	2020	80
2002	18	2020	91
2003	17	2020	86
2004	16	2020	89
2005	15	2020	106

2006	14	2020	105
2007	13	2020	139
2008	12	2020	132
2009	11	2020	132
2010	10	2020	153
2011	9	2020	145
2012	8	2020	126
2013	7	2020	154
2014	6	2020	157
2015	5	2020	203
2016	4	2020	254
2017	3	2020	295
2018	2	2020	395
2019	1	2020	477
2020	0	2020	464

2. By Diagnosis Year

5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1992 - 20 Year			
Death Yr	Lifetime	Dx Year	N
1992	0	1992	332
1993	1	1992	538
1994	2	1992	592
1995	3	1992	447
1996	4	1992	443
1997	5	1992	380
1998	6	1992	338
1999	7	1992	303
2000	8	1992	310
2001	9	1992	255
2002	10	1992	277
2003	11	1992	216
2004	12	1992	171
2005	13	1992	154
2006	14	1992	165
2007	15	1992	157
2008	16	1992	129
2009	17	1992	121
2010	18	1992	123

2011	19	1992	107
2012	20	1992	92

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1993 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1993	0	1993	340
1994	1	1993	493
1995	2	1993	493
1996	3	1993	432
1997	4	1993	348
1998	5	1993	323
1999	6	1993	314
2000	7	1993	273
2001	8	1993	265
2002	9	1993	263
2003	10	1993	224
2004	11	1993	199
2005	12	1993	189
2006	13	1993	159
2007	14	1993	166
2008	15	1993	144
2009	16	1993	141
2010	17	1993	115
2011	18	1993	87
2012	19	1993	82
2013	20	1993	80

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1994 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1994	0	1994	321
1995	1	1994	431
1996	2	1994	392
1997	3	1994	367
1998	4	1994	281
1999	5	1994	290
2000	6	1994	236
2001	7	1994	240
2002	8	1994	199
2003	9	1994	199

2004	10	1994	195
2005	11	1994	193
2006	12	1994	156
2007	13	1994	153
2008	14	1994	125
2009	15	1994	118
2010	16	1994	111
2011	17	1994	102
2012	18	1994	91
2013	19	1994	62
2014	20	1994	67

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1995 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1995	0	1995	297
1996	1	1995	442
1997	2	1995	403
1998	3	1995	306
1999	4	1995	282
2000	5	1995	219
2001	6	1995	224
2002	7	1995	219
2003	8	1995	196
2004	9	1995	163
2005	10	1995	187
2006	11	1995	148
2007	12	1995	159
2008	13	1995	148
2009	14	1995	126
2010	15	1995	124
2011	16	1995	102
2012	17	1995	96
2013	18	1995	78
2014	19	1995	90
2015	20	1995	78

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1996 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**

1996	0	1996	299
1997	1	1996	396
1998	2	1996	390
1999	3	1996	303
2000	4	1996	257
2001	5	1996	236
2002	6	1996	221
2003	7	1996	187
2004	8	1996	200
2005	9	1996	165
2006	10	1996	166
2007	11	1996	144
2008	12	1996	147
2009	13	1996	136
2010	14	1996	120
2011	15	1996	128
2012	16	1996	91
2013	17	1996	89
2014	18	1996	80
2015	19	1996	75
2016	20	1996	78

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1997 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1997	0	1997	291
1998	1	1997	356
1999	2	1997	358
2000	3	1997	288
2001	4	1997	240
2002	5	1997	266
2003	6	1997	237
2004	7	1997	194
2005	8	1997	167
2006	9	1997	173
2007	10	1997	152
2008	11	1997	138
2009	12	1997	158
2010	13	1997	153
2011	14	1997	128
2012	15	1997	109

2013	16	1997	85
2014	17	1997	100
2015	18	1997	93
2016	19	1997	85
2017	20	1997	90

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1998 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1998	0	1998	307
1999	1	1998	387
2000	2	1998	309
2001	3	1998	254
2002	4	1998	260
2003	5	1998	230
2004	6	1998	199
2005	7	1998	215
2006	8	1998	197
2007	9	1998	185
2008	10	1998	162
2009	11	1998	149
2010	12	1998	151
2011	13	1998	130
2012	14	1998	112
2013	15	1998	103
2014	16	1998	109
2015	17	1998	92
2016	18	1998	87
2017	19	1998	85
2018	20	1998	86

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 1999 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1999	0	1999	302
2000	1	1999	371
2001	2	1999	320
2002	3	1999	291
2003	4	1999	267
2004	5	1999	228
2005	6	1999	213

2006	7	1999	223
2007	8	1999	185
2008	9	1999	177
2009	10	1999	164
2010	11	1999	143
2011	12	1999	132
2012	13	1999	120
2013	14	1999	134
2014	15	1999	115
2015	16	1999	128
2016	17	1999	109
2017	18	1999	97
2018	19	1999	112
2019	20	1999	69

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2000 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2000	0	2000	308
2001	1	2000	358
2002	2	2000	351
2003	3	2000	305
2004	4	2000	228
2005	5	2000	245
2006	6	2000	202
2007	7	2000	202
2008	8	2000	175
2009	9	2000	164
2010	10	2000	173
2011	11	2000	155
2012	12	2000	134
2013	13	2000	128
2014	14	2000	120
2015	15	2000	128
2016	16	2000	104
2017	17	2000	119
2018	18	2000	99
2019	19	2000	85
2020	20	2000	64

5-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2001 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2001	0	2001	312
2002	1	2001	323
2003	2	2001	295
2004	3	2001	263
2005	4	2001	238
2006	5	2001	193
2007	6	2001	193
2008	7	2001	202
2009	8	2001	167
2010	9	2001	177
2011	10	2001	157

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2002 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2002	0	2002	325
2003	1	2002	364
2004	2	2002	278
2005	3	2002	283
2006	4	2002	200
2007	5	2002	200
2008	6	2002	174
2009	7	2002	168
2010	8	2002	164
2011	9	2002	139
2012	10	2002	153

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2003 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2003	0	2003	282
2004	1	2003	345
2005	2	2003	316
2006	3	2003	231
2007	4	2003	234

2008	5	2003	217
2009	6	2003	182
2010	7	2003	182
2011	8	2003	159
2012	9	2003	147
2013	10	2003	147

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2004 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2004	0	2004	267
2005	1	2004	365
2006	2	2004	279
2007	3	2004	244
2008	4	2004	216
2009	5	2004	174
2010	6	2004	202
2011	7	2004	171
2012	8	2004	139
2013	9	2004	159
2014	10	2004	133

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2005 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2005	0	2005	347
2006	1	2005	337
2007	2	2005	323
2008	3	2005	251
2009	4	2005	216
2010	5	2005	190
2011	6	2005	170
2012	7	2005	156
2013	8	2005	154
2014	9	2005	137
2015	10	2005	130

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2006 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**

2006	0	2006	342
2007	1	2006	353
2008	2	2006	326
2009	3	2006	256
2010	4	2006	216
2011	5	2006	181
2012	6	2006	171
2013	7	2006	149
2014	8	2006	157
2015	9	2006	154
2016	10	2006	157

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2007 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2007	0	2007	341
2008	1	2007	321
2009	2	2007	270
2010	3	2007	235
2011	4	2007	226
2012	5	2007	204
2013	6	2007	175
2014	7	2007	155
2015	8	2007	180
2016	9	2007	187
2017	10	2007	136

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2008 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2008	0	2008	287
2009	1	2008	325
2010	2	2008	317
2011	3	2008	255
2012	4	2008	192
2013	5	2008	193
2014	6	2008	168
2015	7	2008	150
2016	8	2008	136
2017	9	2008	136
2018	10	2008	159

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2009 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2009	0	2009	321
2010	1	2009	392
2011	2	2009	277
2012	3	2009	258
2013	4	2009	206
2014	5	2009	172
2015	6	2009	192
2016	7	2009	156
2017	8	2009	164
2018	9	2009	175
2019	10	2009	151

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2010 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2010	0	2010	290
2011	1	2010	359
2012	2	2010	271
2013	3	2010	238
2014	4	2010	214
2015	5	2010	172
2016	6	2010	169
2017	7	2010	183
2018	8	2010	163
2019	9	2010	131
2020	10	2010	153

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2011 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2011	0	2011	301
2012	1	2011	370
2013	2	2011	292
2014	3	2011	239
2015	4	2011	192
2016	5	2011	195

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2012 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2012	0	2012	304
2013	1	2012	355
2014	2	2012	268
2015	3	2012	212
2016	4	2012	194
2017	5	2012	180

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2013 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2013	0	2013	332
2014	1	2013	400
2015	2	2013	308
2016	3	2013	301
2017	4	2013	201
2018	5	2013	179

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2014 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2014	0	2014	387
2015	1	2014	369
2016	2	2014	347
2017	3	2014	244
2018	4	2014	228
2019	5	2014	177

Number of Cause-specific Deaths Based on Diagnoses of Prostate Cancer Patients in 2015 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2015	0	2015	379
2016	1	2015	446

2017	2	2015	336
2018	3	2015	338
2019	4	2015	233
2020	5	2015	203

D. Breast Cancer Raw Data

1. By Death Year

Number of Cause-specific Deaths of Breast Cancer Patients in 1997 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1992	5	1997	365
1993	4	1997	443
1994	3	1997	553
1995	2	1997	624
1996	1	1997	673
1997	0	1997	453

Number of Cause-specific Deaths of Breast Cancer Patients in 1998 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1993	5	1998	388
1994	4	1998	478
1995	3	1998	575
1996	2	1998	673
1997	1	1998	680
1998	0	1998	462

Number of Cause-specific Deaths of Breast Cancer Patients in 1999 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1994	5	1999	359
1995	4	1999	436
1996	3	1999	542

1997	2	1999	623
1998	1	1999	609
1999	0	1999	442

Number of Cause-specific Deaths of Breast Cancer Patients in 2000 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1995	5	2000	345
1996	4	2000	452
1997	3	2000	531
1998	2	2000	630
1999	1	2000	593
2000	0	2000	426

Number of Cause-specific Deaths of Breast Cancer Patients in 2001 - 5 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1996	5	2001	357
1997	4	2001	447
1998	3	2001	602
1999	2	2001	600
2000	1	2001	622
2001	0	2001	483

The remaining 5-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Breast Cancer Patients in 2002 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1992	10	2002	158
1993	9	2002	185
1994	8	2002	225
1995	7	2002	264
1996	6	2002	287
1997	5	2002	340
1998	4	2002	438
1999	3	2002	545
2000	2	2002	589

2001	1	2002	599
2002	0	2002	424

Number of Cause-specific Deaths of Breast Cancer Patients in 2003 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1993	10	2003	162
1994	9	2003	202
1995	8	2003	219
1996	7	2003	266
1997	6	2003	320
1998	5	2003	358
1999	4	2003	462
2000	3	2003	503
2001	2	2003	606
2002	1	2003	584
2003	0	2003	452

Number of Cause-specific Deaths of Breast Cancer Patients in 2004 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1994	10	2004	225
1995	9	2004	213
1996	8	2004	246
1997	7	2004	255
1998	6	2004	341
1999	5	2004	408
2000	4	2004	420
2001	3	2004	524
2002	2	2004	618
2003	1	2004	591
2004	0	2004	434

Number of Cause-specific Deaths of Breast Cancer Patients in 2005 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1995	10	2005	174
1996	9	2005	207

1997	8	2005	239
1998	7	2005	258
1999	6	2005	335
2000	5	2005	374
2001	4	2005	427
2002	3	2005	532
2003	2	2005	577
2004	1	2005	614
2005	0	2005	450

Number of Cause-specific Deaths of Breast Cancer Patients in 2006 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1996	10	2006	178
1997	9	2006	199
1998	8	2006	257
1999	7	2006	276
2000	6	2006	324
2001	5	2006	404
2002	4	2006	426
2003	3	2006	501
2004	2	2006	613
2005	1	2006	560
2006	0	2006	405

Number of Cause-specific Deaths of Breast Cancer Patients in 2007 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1997	10	2007	183
1998	9	2007	191
1999	8	2007	234
2000	7	2007	287
2001	6	2007	291
2002	5	2007	373
2003	4	2007	398
2004	3	2007	503
2005	2	2007	564
2006	1	2007	569
2007	0	2007	462

Number of Cause-specific Deaths of Breast Cancer Patients in 2008 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1998	10	2008	188
1999	9	2008	203
2000	8	2008	248
2001	7	2008	294
2002	6	2008	322
2003	5	2008	354
2004	4	2008	427
2005	3	2008	485
2006	2	2008	571
2007	1	2008	580
2008	0	2008	422

Number of Cause-specific Deaths of Breast Cancer Patients in 2009 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1999	10	2009	208
2000	9	2009	222
2001	8	2009	263
2002	7	2009	272
2003	6	2009	303
2004	5	2009	350
2005	4	2009	408
2006	3	2009	527
2007	2	2009	566
2008	1	2009	562
2009	0	2009	443

Number of Cause-specific Deaths of Breast Cancer Patients in 2010 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
2000	10	2010	192
2001	9	2010	190
2002	8	2010	220
2003	7	2010	230

2004	6	2010	296
2005	5	2010	373
2006	4	2010	414
2007	3	2010	529
2008	2	2010	623
2009	1	2010	602
2010	0	2010	453

Number of Cause-specific Deaths of Breast Cancer Patients in 2011 - 10 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
2001	10	2011	156
2002	9	2011	198
2003	8	2011	234
2004	7	2011	252
2005	6	2011	294
2006	5	2011	319
2007	4	2011	423
2008	3	2011	504
2009	2	2011	605
2010	1	2011	592
2011	0	2011	453

The remaining 5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths of Breast Cancer Patients in 2012 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1992	20	2012	72
1993	19	2012	72
1994	18	2012	72
1995	17	2012	110
1996	16	2012	101
1997	15	2012	126
1998	14	2012	127
1999	13	2012	134
2000	12	2012	131
2001	11	2012	171
2002	10	2012	173

2003	9	2012	182
2004	8	2012	199
2005	7	2012	276
2006	6	2012	293
2007	5	2012	355
2008	4	2012	442
2009	3	2012	534
2010	2	2012	601
2011	1	2012	564
2012	0	2012	443

Number of Cause-specific Deaths of Breast Cancer Patients in 2013 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1993	20	2013	69
1994	19	2013	70
1995	18	2013	72
1996	17	2013	75
1997	16	2013	95
1998	15	2013	107
1999	14	2013	115
2000	13	2013	96
2001	12	2013	140
2002	11	2013	151
2003	10	2013	178
2004	9	2013	191
2005	8	2013	184
2006	7	2013	250
2007	6	2013	303
2008	5	2013	366
2009	4	2013	430
2010	3	2013	534
2011	2	2013	610
2012	1	2013	617
2013	0	2013	477

Number of Cause-specific Deaths of Breast Cancer Patients in 2014 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1994	20	2014	54

1995	19	2014	66
1996	18	2014	94
1997	17	2014	88
1998	16	2014	96
1999	15	2014	103
2000	14	2014	103
2001	13	2014	138
2002	12	2014	156
2003	11	2014	138
2004	10	2014	141
2005	9	2014	187
2006	8	2014	216
2007	7	2014	237
2008	6	2014	299
2009	5	2014	315
2010	4	2014	411
2011	3	2014	522
2012	2	2014	631
2013	1	2014	652
2014	0	2014	528

Number of Cause-specific Deaths of Breast Cancer Patients in 2015 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1995	20	2015	69
1996	19	2015	82
1997	18	2015	86
1998	17	2015	96
1999	16	2015	86
2000	15	2015	92
2001	14	2015	91
2002	13	2015	120
2003	12	2015	134
2004	11	2015	159
2005	10	2015	137
2006	9	2015	200
2007	8	2015	219
2008	7	2015	281
2009	6	2015	303
2010	5	2015	352
2011	4	2015	453

2012	3	2015	533
2013	2	2015	576
2014	1	2015	650
2015	0	2015	506

Number of Cause-specific Deaths of Breast Cancer Patients in 2016 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1996	20	2016	74
1997	19	2016	89
1998	18	2016	81
1999	17	2016	89
2000	16	2016	97
2001	15	2016	119
2002	14	2016	133
2003	13	2016	127
2004	12	2016	141
2005	11	2016	167
2006	10	2016	161
2007	9	2016	195
2008	8	2016	222
2009	7	2016	251
2010	6	2016	289
2011	5	2016	398
2012	4	2016	417
2013	3	2016	535
2014	2	2016	584
2015	1	2016	627
2016	0	2016	492

Number of Cause-specific Deaths of Breast Cancer Patients in 2017 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1997	20	2017	71
1998	19	2017	77
1999	18	2017	84
2000	17	2017	90
2001	16	2017	98
2002	15	2017	103
2003	14	2017	100

2004	13	2017	117
2005	12	2017	133
2006	11	2017	142
2007	10	2017	181
2008	9	2017	196
2009	8	2017	247
2010	7	2017	269
2011	6	2017	311
2012	5	2017	385
2013	4	2017	407
2014	3	2017	516
2015	2	2017	621
2016	1	2017	676
2017	0	2017	472

Number of Cause-specific Deaths of Breast Cancer Patients in 2018 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1998	20	2018	77
1999	19	2018	76
2000	18	2018	88
2001	17	2018	97
2002	16	2018	76
2003	15	2018	103
2004	14	2018	114
2005	13	2018	125
2006	12	2018	123
2007	11	2018	151
2008	10	2018	166
2009	9	2018	192
2010	8	2018	218
2011	7	2018	281
2012	6	2018	285
2013	5	2018	362
2014	4	2018	445
2015	3	2018	505
2016	2	2018	588
2017	1	2018	641
2018	0	2018	519

Number of Cause-specific Deaths of Breast Cancer Patients in 2019 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
1999	20	2019	84
2000	19	2019	53
2001	18	2019	85
2002	17	2019	71
2003	16	2019	94
2004	15	2019	118
2005	14	2019	98
2006	13	2019	121
2007	12	2019	133
2008	11	2019	183
2009	10	2019	197
2010	9	2019	204
2011	8	2019	226
2012	7	2019	229
2013	6	2019	264
2014	5	2019	358
2015	4	2019	450
2016	3	2019	482
2017	2	2019	605
2018	1	2019	630
2019	0	2019	515

Number of Cause-specific Deaths of Breast Cancer Patients in 2020 - 20 Year			
Dx Year	**Lifetime**	**Death Year**	**N**
2000	20	2020	62
2001	19	2020	92
2002	18	2020	83
2003	17	2020	76
2004	16	2020	91
2005	15	2020	97
2006	14	2020	113
2007	13	2020	117
2008	12	2020	118
2009	11	2020	160
2010	10	2020	160
2011	9	2020	180

2012	8	2020	254
2013	7	2020	267
2014	6	2020	276
2015	5	2020	372
2016	4	2020	418
2017	3	2020	518
2018	2	2020	576
2019	1	2020	679
2020	0	2020	519

2. By Diagnosis Year

5-year and 10-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1992 - 20 Year			
Death Yr	Lifetime	Dx Year	N
1992	0	1992	408
1993	1	1992	617
1994	2	1992	638
1995	3	1992	591
1996	4	1992	446
1997	5	1992	365
1998	6	1992	307
1999	7	1992	244
2000	8	1992	205
2001	9	1992	174
2002	10	1992	158
2003	11	1992	158
2004	12	1992	120
2005	13	1992	135
2006	14	1992	116
2007	15	1992	98
2008	16	1992	99
2009	17	1992	79
2010	18	1992	79
2011	19	1992	72
2012	20	1992	72

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1993 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**

1993	0	1993	418
1994	1	1993	579
1995	2	1993	661
1996	3	1993	567
1997	4	1993	443
1998	5	1993	388
1999	6	1993	309
2000	7	1993	236
2001	8	1993	241
2002	9	1993	185
2003	10	1993	162
2004	11	1993	156
2005	12	1993	120
2006	13	1993	128
2007	14	1993	120
2008	15	1993	101
2009	16	1993	98
2010	17	1993	70
2011	18	1993	67
2012	19	1993	72
2013	20	1993	69

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1994 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1994	0	1994	364
1995	1	1994	646
1996	2	1994	702
1997	3	1994	553
1998	4	1994	478
1999	5	1994	359
2000	6	1994	287
2001	7	1994	223
2002	8	1994	225
2003	9	1994	202
2004	10	1994	225
2005	11	1994	157
2006	12	1994	169
2007	13	1994	120
2008	14	1994	110
2009	15	1994	96
2010	16	1994	87

2011	17	1994	91
2012	18	1994	72
2013	19	1994	70
2014	20	1994	54

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1995 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1995	0	1995	404
1996	1	1995	667
1997	2	1995	624
1998	3	1995	575
1999	4	1995	436
2000	5	1995	345
2001	6	1995	304
2002	7	1995	264
2003	8	1995	219
2004	9	1995	213
2005	10	1995	174
2006	11	1995	174
2007	12	1995	144
2008	13	1995	105
2009	14	1995	125
2010	15	1995	104
2011	16	1995	99
2012	17	1995	110
2013	18	1995	72
2014	19	1995	66
2015	20	1995	69

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1996 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1996	0	1996	412
1997	1	1996	673
1998	2	1996	673
1999	3	1996	542
2000	4	1996	452
2001	5	1996	357
2002	6	1996	287

2003	7	1996	266
2004	8	1996	246
2005	9	1996	207
2006	10	1996	178
2007	11	1996	152
2008	12	1996	154
2009	13	1996	135
2010	14	1996	129
2011	15	1996	103
2012	16	1996	101
2013	17	1996	75
2014	18	1996	94
2015	19	1996	82
2016	20	1996	74

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1997 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1997	0	1997	453
1998	1	1997	680
1999	2	1997	623
2000	3	1997	531
2001	4	1997	447
2002	5	1997	340
2003	6	1997	320
2004	7	1997	255
2005	8	1997	239
2006	9	1997	199
2007	10	1997	183
2008	11	1997	161
2009	12	1997	167
2010	13	1997	153
2011	14	1997	140
2012	15	1997	126
2013	16	1997	95
2014	17	1997	88
2015	18	1997	86
2016	19	1997	89
2017	20	1997	71

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1998 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1998	0	1998	462
1999	1	1998	609
2000	2	1998	630
2001	3	1998	602
2002	4	1998	438
2003	5	1998	358
2004	6	1998	341
2005	7	1998	258
2006	8	1998	257
2007	9	1998	191
2008	10	1998	188
2009	11	1998	160
2010	12	1998	165
2011	13	1998	123
2012	14	1998	127
2013	15	1998	107
2014	16	1998	96
2015	17	1998	96
2016	18	1998	81
2017	19	1998	77
2018	20	1998	77

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 1999 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
1999	0	1999	442
2000	1	1999	593
2001	2	1999	600
2002	3	1999	545
2003	4	1999	462
2004	5	1999	408
2005	6	1999	335
2006	7	1999	276
2007	8	1999	234
2008	9	1999	203
2009	10	1999	208
2010	11	1999	157
2011	12	1999	146

2012	13	1999	134
2013	14	1999	115
2014	15	1999	103
2015	16	1999	86
2016	17	1999	89
2017	18	1999	84
2018	19	1999	76
2019	20	1999	84

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2000 - 20 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2000	0	2000	426
2001	1	2000	622
2002	2	2000	589
2003	3	2000	503
2004	4	2000	420
2005	5	2000	374
2006	6	2000	324
2007	7	2000	287
2008	8	2000	248
2009	9	2000	222
2010	10	2000	192
2011	11	2000	140
2012	12	2000	131
2013	13	2000	96
2014	14	2000	103
2015	15	2000	92
2016	16	2000	97
2017	17	2000	90
2018	18	2000	88
2019	19	2000	53
2020	20	2000	62

5-year tables are embedded in the tables below.

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2001 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2001	0	2001	483

2002	1	2001	599
2003	2	2001	606
2004	3	2001	524
2005	4	2001	427
2006	5	2001	404
2007	6	2001	291
2008	7	2001	294
2009	8	2001	263
2010	9	2001	190
2011	10	2001	156

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2002 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2002	0	2002	424
2003	1	2002	584
2004	2	2002	618
2005	3	2002	532
2006	4	2002	426
2007	5	2002	373
2008	6	2002	322
2009	7	2002	272
2010	8	2002	220
2011	9	2002	198
2012	10	2002	173

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2003 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2003	0	2003	452
2004	1	2003	591
2005	2	2003	577
2006	3	2003	501
2007	4	2003	398
2008	5	2003	354
2009	6	2003	303
2010	7	2003	230
2011	8	2003	234
2012	9	2003	182

2013	10	2003	178

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2004 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2004	0	2004	434
2005	1	2004	614
2006	2	2004	613
2007	3	2004	503
2008	4	2004	427
2009	5	2004	350
2010	6	2004	296
2011	7	2004	252
2012	8	2004	199
2013	9	2004	191
2014	10	2004	141

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2005 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2005	0	2005	450
2006	1	2005	560
2007	2	2005	564
2008	3	2005	485
2009	4	2005	408
2010	5	2005	373
2011	6	2005	294
2012	7	2005	276
2013	8	2005	184
2014	9	2005	187
2015	10	2005	137

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2006 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2006	0	2006	405
2007	1	2006	569
2008	2	2006	571
2009	3	2006	527
2010	4	2006	414
2011	5	2006	319

2012	6	2006	293
2013	7	2006	250
2014	8	2006	216
2015	9	2006	200
2016	10	2006	161

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2007 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2007	0	2007	462
2008	1	2007	580
2009	2	2007	566
2010	3	2007	529
2011	4	2007	423
2012	5	2007	355
2013	6	2007	303
2014	7	2007	237
2015	8	2007	219
2016	9	2007	195
2017	10	2007	181

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2008 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2008	0	2008	422
2009	1	2008	562
2010	2	2008	623
2011	3	2008	504
2012	4	2008	442
2013	5	2008	366
2014	6	2008	299
2015	7	2008	281
2016	8	2008	222
2017	9	2008	196
2018	10	2008	166

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2009 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2009	0	2009	443

2010	1	2009	602
2011	2	2009	605
2012	3	2009	534
2013	4	2009	430
2014	5	2009	315
2015	6	2009	303
2016	7	2009	251
2017	8	2009	247
2018	9	2009	192
2019	10	2009	197

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2010 - 10 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2010	0	2020	453
2011	1	2020	592
2012	2	2020	601
2013	3	2020	534
2014	4	2020	411
2015	5	2020	352
2016	6	2020	289
2017	7	2020	269
2018	8	2020	218
2019	9	2020	204
2020	10	2020	160

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2011 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2011	0	2011	453
2012	1	2011	564
2013	2	2011	610
2014	3	2011	522
2015	4	2011	453
2016	5	2011	398

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2012 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**

2012	0	2012	443
2013	1	2012	617
2014	2	2012	631
2015	3	2012	533
2016	4	2012	417
2017	5	2012	385

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2013 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2013	0	2013	477
2014	1	2013	652
2015	2	2013	576
2016	3	2013	535
2017	4	2013	407
2018	5	2013	362

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2014 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2014	0	2014	528
2015	1	2014	650
2016	2	2014	584
2017	3	2014	516
2018	4	2014	445
2019	5	2014	358

Number of Cause-specific Deaths Based on Diagnoses of Breast Cancer Patients in 2015 - 5 Year			
Death Yr	**Lifetime**	**Dx Year**	**N**
2015	0	2015	506
2016	1	2015	627
2017	2	2015	621
2018	3	2015	505
2019	4	2015	450
2020	5	2015	372

F. Sample Code

Note, all sample code was developed by and obtained from Daniel Berleant, PhD.

Exponential

```
<!DOCTYPE html>
<html>
<head>
<title>Exponential</title>
</head>
<body>

<h1>Data from SEER Nov 2022 Sub (1992-2020) Database - 20 Year Cause-Specific Survival Time of Kidney & Renal Cancer Patients That Died in Years 2012-2020</h1>
<h2>Exponential Model</h2>
<h3>T0=<span id="T0">[Error 98: The value of T0 should appear here.]</span></h3>
<h3>lifeAtT0          = <span id="lifeAtT0">Error 99: not yet initialized</span></h3> <!-If set manually, the number will be shown here->
<h3><i>Model update of 7/16/2024</i></h3>


<button onclick='if (typeof lifeAtT0!=="number")
            alert(`lifeAtT0 is not a number. Set it to one to use this button. Hint: also set T0.`);
                        else{
            document.getElementById("log").innerHTML="";
            searchDforMinSSR();}'>
        Click to find the line with the value of <b>doubling time</b> yielding the best fit (lowest SSR) for a given lifeAtT0
</button>
<br><br>
<button onclick='if (lifeAtT0!=="Determined algorithmically")
            alert(`lifeAtT0 is a number. Set it to the string "Determined algorithmically" instead.`);
                        else{
            document.getElementById("log").innerHTML="";
            searchDforMinSSR();}'>
        Click to find the line with the <b>doubling time</b> and <b>lifeAtT0</b> yielding the best fit (lowest SSR)
</button>
<br><br>

<button onclick="document.getElementById('log').innerHTML='';
            searchCforMinSSRmultipass(parseInt(prompt('Type value for d:'), 10),
                                      cStart);">
        Click to find the exponential curve with a given doubling time d and the c yielding the best fit for that d
</button>
<br><br>
```

```
<button onclick="document.getElementById('log').innerHTML='';
            log('SSR = ' + fillInSSR(parseInt  (prompt('Type value for d:'), 10),
                                parseFloat(prompt('Type value for c:'), 10)
                                                                ).SSR
                                        );">
        Click to input the doubling time d and start value c, and find the SSR
</button>

<p id="log"></p>
<script>
let lifeAtT0 = "Determined algorithmically"; //Set it manually by changing this line to a number
document.getElementById("lifeAtT0").innerHTML = lifeAtT0;
const cIncrementFactor          = 2;     //Must be > 1. When searching for the c with minimum
SSR, multiply c by this constant each iteration
const cIncrementFactorRefinement = 5;     //Must be > 1. Make cIncrementFactor this many
times closer to 1.
const cIncrementFactorThreshold  = 1.001; //If cIncrementFactor decreases below the
threshold, it is small enough to produce accurate enough results
const cStart                    = 0.001; //0.001 undercuts the c with min SSR even for slope=1, but
higher values will speed things up
const T0 = 1990;
document.getElementById("T0").innerHTML=T0;

logLifetimeData      = {        name : "LogLifetimeData",
                      populate : // Initialize dataTable's column of lifetime data log values
("LogLifetimeData")
  function(){
    for (dataTableIndex=0; dataTableIndex<dataTable.lifetimeData.length; dataTableIndex++){

dataTable.logLifetimeData[dataTableIndex]=Math.log2(dataTable.lifetimeData[dataTableIndex]);
    }
  }
}
predictedLifetimes   = {        name : "PredictedLifetimes",
                    doublingTime : 11,     //initial guess
                            T0 : T0,     //taken from the global constant
                                        lifetimeAtT0 : 0.5,    //initial guess
                                                populate : // Calculate dataTable's column of
lifetime predictions from fail dates (predictedLifetimes)
  function (){
    //alert("### "+predictedLifetimes.lifetimeAtT0);
          for (dataTableIndex=0; dataTableIndex<dataTable.endYear.length; dataTableIndex++){
      dataTable.predictedLifetimes[dataTableIndex]
        =lifetimeFromFaildateAnyT0(dataTable.endYear[dataTableIndex],
                                  predictedLifetimes.doublingTime,
                                          predictedLifetimes.lifetimeAtT0,
                              predictedLifetimes.T0);
    }
  }
}
```

```
logPredictedLifetimes= {       name : "LogPredictedLifetime",
                        populate : // Calculate dataTable's column of logs of lifetime predictions
("LogPredictedLifetimes")
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.predictedLifetimes.length;
dataTableIndex++){
      dataTable.logPredictedLifetimes[dataTableIndex]
        =Math.log2(dataTable.predictedLifetimes[dataTableIndex]);
    }
  }
}

fittingErrors       = {       name: "FittingErrors",
                        populate : // Calculate dataTable's column of fitting errors between lifetime data
and lifetime model ("fittingErrors")
  function calcFittingErrors(){
    for (dataTableIndex=0; dataTableIndex<dataTable.logPredictedLifetimes.length;
dataTableIndex++){
            dataTable.fittingErrors[dataTableIndex]
              = dataTable.logPredictedLifetimes[dataTableIndex] <
dataTable.logLifetimeData[dataTableIndex]
                  ?
                  (dataTable.logLifetimeData[dataTableIndex] -
dataTable.logPredictedLifetimes[dataTableIndex])
                        :
                        (dataTable.logPredictedLifetimes[dataTableIndex] -
dataTable.logLifetimeData[dataTableIndex])
    }
  }
}
squaredFittingErrors = {       name : "SquaredFittingErrors",
                          SSR : "uninitialized",
                                                  populate : // Calculate dataTable's column of
squared fitting errors (squaredFittingErrors)
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.fittingErrors.length; dataTableIndex++){
      dataTable.squaredFittingErrors[dataTableIndex]
        =dataTable.fittingErrors[dataTableIndex]**2;
    }
  },                    calcSSR : // Calculate SSR
  function (){
    squaredFittingErrors.SSR=0;
    for (dataTableIndex=0; dataTableIndex<dataTable.squaredFittingErrors.length;
dataTableIndex++){
                  squaredFittingErrors.SSR += dataTable.squaredFittingErrors[dataTableIndex];
    }
  }
}
predictedStartDates = {       name : "PredictedStartDates",
                        populate : // Calculate dataTable's column of start dates
("predictedStartDates")
```

```
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.predictedLifetimes.length;
dataTableIndex++){
      dataTable.predictedStartDates[dataTableIndex]
        = dataTable.endYear[dataTableIndex] - dataTable.predictedLifetimes[dataTableIndex];
    }
  }
}

let dataTable = {
  key               : [2012 , 2013 , 2014 , 2015 , 2016 , 2017 , 2018 , 2019 , 2020],
  endYear           : [2012 , 2013 , 2014 , 2015 , 2016 , 2017 , 2018 , 2019 , 2020],
  lifetimeData      : [3.379 ,3.289 ,3.256 ,3.363 ,3.579 ,3.571 ,3.760 ,3.861 ,3.636],
  logLifetimeData   : [], //to be initialized once
  predictedLifetimes  : [], //to be calculated by the regression process
  logPredictedLifetimes: [], //to be calculated by the regression process
  fittingErrors     : [], //to be calculated by the regression process
  squaredFittingErrors : [], //to be calculated by the regression process
  predictedStartDates  : []  //to be calculated by the regression process
}
logLifetimeData.populate(); //Calculate once as part of initialization.

function updateDataTableFromModelParams(){
  predictedLifetimes  .populate();
  logPredictedLifetimes.populate();
  fittingErrors     .populate();
  squaredFittingErrors .populate(); squaredFittingErrors.calcSSR();
  predictedStartDates  .populate();
}
updateDataTableFromModelParams();

function fillInSSR(d, c){
  predictedLifetimes.doublingTime = d;
  predictedLifetimes.lifetimeAtT0 = c;
  updateDataTableFromModelParams();
  return({d : d, c : c, SSR : squaredFittingErrors.SSR});
}

function searchCforSSRdip1pass(d, c, cIncrement){
  let dataPointLc, dataPointMc, dataPointHc, dataPointTemp;
  dataPointLc = fillInSSR(d, c);
  dataPointMc = fillInSSR(d, c*=cIncrement);
  while(true){
        dataPointHc = fillInSSR(d, c*=cIncrement);
    if (dataPointLc.SSR < dataPointMc.SSR) {log("<hr><b>Warning</b>, dataPointLc.SSR <
dataPointMc.SSR in searchCforSSRdip1pass: d="+d+",
cIncrement="+cIncrement+",<br>dataPointLc .c="+dataPointLc.c+", dataPointLc
.SSR="+dataPointLc.SSR+"<br>dataPointMc.c="+dataPointMc.c+",
dataPointMc.SSR="+dataPointMc.SSR);break;}
      else if (dataPointMc.SSR < dataPointHc.SSR) {break;} //The min SSR occurs somewhere
between L(ow) and H(igh) values of calcFittingErrors
```

```
      else {dataPointTemp = dataPointLc;
                dataPointLc   = dataPointMc;
           dataPointMc   = dataPointHc;
                     dataPointHc   = null;
                    }
   }
        fillInSSR(dataPointMc.d, dataPointMc.c); //Make dataTable reflect dip, not H after the dip
        return({dataPointLc : dataPointLc, dataPointMc : dataPointMc, dataPointHc :
dataPointHc});
}

function searchCforMinSSRmultipass(d, loBoundC){
  let cIncrement = cIncrementFactor;
                                                                    //if cIncrement is 2, and
cIncrementFactorRefinement is 5, then the updated cIncrement is 1.2
  for (cIncrement ; cIncrement>cIncrementFactorThreshold ; cIncrement=1+(cIncrement-
1)/cIncrementFactorRefinement){
    loBoundC = searchCforSSRdip1pass(d, loBoundC, cIncrement).dataPointLc.c;
  }
  let u = searchCforSSRdip1pass(d, loBoundC, cIncrement); //u is set to the three data points of
the u-shaped dip
  log("<hr>Here is the region of c giving lowest SSR for d="+d+":");
  log("For c="+u.dataPointLc.c+", SSR="+u.dataPointLc.SSR);
  log("For c="+u.dataPointMc.c+", SSR="+u.dataPointMc.SSR+" <b>(best)</b>");
  log("For c="+u.dataPointHc.c+", SSR="+u.dataPointHc.SSR);
  return(u.dataPointMc);
}

function getLifeAtT0byDispatch(d){
  if (lifeAtT0 === "Determined algorithmically")
    return searchCforMinSSRmultipass(d, cStart);
  else if (typeof lifeAtT0 === "number")
          return fillInSSR(d, lifeAtT0);
  else alert("Error 101: lifeAtT0 === " + lifeAtT0 + ": bad value");
}
function searchDforMinSSR(){
  let dataPointLd = getLifeAtT0byDispatch(1);
  let dataPointMd = getLifeAtT0byDispatch(2);
  let dataPointHd = getLifeAtT0byDispatch(3);
  let nextD;
  if (dataPointLd.SSR < dataPointMd.SSR) { //Presumably, d=1 is not better than d=2, but check
anyway
    log("Probably an error, as d<2 seems unlikely.");
  };
  for (nextD = dataPointHd.d+1 ; dataPointMd.SSR > dataPointHd.SSR ; nextD++){
          dataPointLd = dataPointMd;
          dataPointMd = dataPointHd;
          dataPointHd = getLifeAtT0byDispatch(nextD);  //Could use a number above cStart for
efficiency, since d<>1 here, I think
  }
  fillInSSR(dataPointMd.d, dataPointMd.c); //Make dataTable reflect the dip, not H after the dip
```

```
  log("<hr><hr><b>Summary: here is the region of best d (that is, the d with lowest SSR):</b>");
  log("For doubling time d just below the best value, d="+dataPointLd.d+",    c with lowest SSR
is "+dataPointLd.c+" with SSR="+dataPointLd.SSR);
  log('<span style="background-color: yellow;");><b>For doubling time d that is best, d=' +
dataPointMd.d + ", c with lowest SSR is " + dataPointMd.c + " and SSR=" + dataPointMd.SSR +
" (best d and c with lowest SSR!)</span>");
  log(  '<span style="background-color: yellow;"><b>'
     + "Equation of best fit curve is:        <b>"
          + " x = " + T0 + " + y + " + dataPointMd.d + "*log2(y/" + dataPointMd.c + ")"
          + "         where x is the
INdependent variable despite the form of the equation."
          + "</span>");
  for (let i=0; i<dataTable.endYear.length; i++){
    log(  '       <span style="background-color:
yellow;"><b>'
       + "For end year " + dataTable.endYear[i] + ", ave. lifetime = " + dataTable.lifetimeData[i]
       + ", regressed model prediction = " + dataTable.predictedLifetimes[i]
            + "</span>"); };
  log("       Next line checks previous line:
predictions should be equal.");
  {let firstFutureYear = dataTable.endYear[dataTable.endYear.length-1];
   for (let i=firstFutureYear ; i<=firstFutureYear+50 ; i++){
       log(  '       <span style="background-color:
yellow;"><b>'
          + "For end year " + i + ", ave. lifetime = (data not present), regressed model prediction
= "
          + lifetimeFromFaildateAnyT0(i, dataPointMd.d, dataPointMd.c, T0)
          + "</span>");
   }
  }
  log("For doubling time d just above the best value, d="+dataPointHd.d+",    c with lowest SSR
is "+dataPointHd.c+" with SSR="+dataPointHd.SSR);
  // return(dataPointMd.d); //Not used, so why return it.
}

function log(messageLine){
  document.getElementById("log").innerHTML+=messageLine+"<br>";
}


// *** Use bisection method ***
function lifetimeFromFaildateAnyT0(failDate, doublingTime, lifetimeAtT0, yearOfT0) {
 //alert("faildate="+failDate+"  doublingTime="+doublingTime+"  lifetimeAtT0="+lifetimeAtT0+"
yearOfT0="+yearOfT0);
 const minLife=.0005, maxLife=1000000, envelope=0.00001;
 var loBound=minLife, hiBound=maxLife, guessedLife=(hiBound+loBound)/2;

 if (doublingTime===0) return "Error, doubling time cannot be zero.";
 if (doublingTime<0) return "Error, negative doubling times can lead to two answers, and this
function doesn't do that.";
```

```
  if ((typeof failDate!=="number")||(typeof doublingTime!=="number")||(typeof
lifetimeAtT0!=="number")) return "error, nonnumeric arg(s)";

  while ((hiBound-loBound)>envelope){
     ((yearOfT0+guessedLife+doublingTime*Math.log2(guessedLife/lifetimeAtT0)) //This is the
eq. for lifetime given fail date
       <
       failDate
     )
       ? loBound=guessedLife
       : hiBound=guessedLife;
     guessedLife=(hiBound+loBound)/2;
  }
  if (guessedLife <= minLife+envelope) return "error, lifetime not found, approaching low bound";
  else if (guessedLife >= maxLife-envelope) return "error, lifetime not found, approaching high
bound";
  else return guessedLife; //Has converged on the answer
}
</script>

</body>
</html>
```

Linear

```
<!DOCTYPE html>
<html>
<head>
<title>KC Curve fitting</title>
</head>
<body>

<h1>Data from SEER Nov 2022 Sub (1992-2020) Database - 20 Year Cause-Specific Survival
Time of Kidney and Renal Pelvis Cancer Patients That Died in Years 2012-2020</h1>

<h2><pre>
<u>Linear Model</u>:
lifetime(startTime) =  slope*(startTime - T0) + lifetimeAtT0
lifetime(endTime)   = (slope*(  endTime - T0) + lifetimeAtT0)/(slope + 1)
T0                  = <span id="T0">Error 98: The value of T0 should be shown here.</span>
lifeAtT0            = <span id="lifeAtT0">Error 99: not yet initialized</span> <!-If set manually, the
number will be shown here->
</pre>
</h2>
<h3><i>Model update of 7/16/2024</i></h3>


<button onclick='if (typeof lifeAtT0!=="number")
                 alert(`lifeAtT0 is not a number. Set it to one to use this button. Hint: also set T0.`);
                                    else{
```

```
            document.getElementById("log").innerHTML="";
            searchSlopeforMinSSR();}'>
        Click to find the line with the value of <b>slope</b> yielding the best fit (lowest SSR) for
a given lifeAtT0
</button>
<br><br>
<button onclick='if (lifeAtT0!=="Determined algorithmically")
            alert(`lifeAtT0 is a number. Set it to the string "Determined algorithmically"
instead.`);
                                    else{
            document.getElementById("log").innerHTML="";
            searchSlopeforMinSSR();}'>
        Click to find the line with the values of <b>slope</b> and <b>lifeAtT0</b> yielding the
best fit (lowest SSR)
</button>
<br><br>

<button onclick="document.getElementById('log').innerHTML='';
            searchLifeAtT0forMinSSRmultipass(parseFloat(prompt('Type value for slope:'), 10),
                                                    lifeAtT0min);">
        Click to find the line with a given slope and the lifeAtT0 yielding the best fit for that slope
</button>
<br><br>

<button onclick="document.getElementById('log').innerHTML='';
            log('SSR = ' + fillInSSR(parseFloat (prompt('Type value for slope:'), 10),
                            parseFloat (prompt('Type value for lifeAtT0:'), 10)
                                                    ).SSR
                                    );">
        Click to input the slope and start value lifeAtT0, and find the SSR
</button>

<p id="log"></p>

<script>
let lifeAtT0 = "Determined algorithmically"; //Set it manually by changing this line to a number
document.getElementById("lifeAtT0").innerHTML = lifeAtT0;
const lifeAtT0incrementFactor          = 2;     //Must be > 1. When searching for the c with
minimum SSR, multiply c by this constant each iteration
const lifeAtT0incrementFactorRefinement = 5;     //Must be > 1. Make lifeAtT0incrementFactor
this many times closer to 1.
const lifeAtT0incrementFactorMin       = 1.001; //If lifeAtT0incrementFactor decreases below the
threshold, it is small enough to produce accurate enough results
const lifeAtT0min                      = 0.001; //Should be low enough to undercut the lifeAtT0 values
with min SSR for any slope, but higher values will speed things up
const minPosSlope = 0.0001;
const slopeIncrement = 1.05; //Is this so close to 1 that numerical error could cause a false
trough in SSR? Hopefully not.
const T0 = 1990;
document.getElementById("T0").innerHTML=T0;
```

```
logLifetimeData      = {       name : "LogLifetimeData",
                      populate : // Initialize dataTable's column of lifetime data log values
("LogLifetimeData")
  function(){
    for (dataTableIndex=0; dataTableIndex<dataTable.lifetimeData.length; dataTableIndex++){

dataTable.logLifetimeData[dataTableIndex]=Math.log2(dataTable.lifetimeData[dataTableIndex]);
    }
  }
}
predictedLifetimes   = {       name : "PredictedLifetimes",
                       slope : 0.1               , //initial guess
                         T0 : T0                 , //taken from the global constant
                                                   lifeAtT0 : 0.5               , //initial guess
                                                         populate : // Calculate dataTable's column of
lifetime predictions from fail dates,
                               // i.e., predictedLifetimes
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.endYear.length; dataTableIndex++){
      dataTable.predictedLifetimes[dataTableIndex]
        =lifetimeFromFaildateAnyT0(dataTable.endYear[dataTableIndex],
                                   predictedLifetimes.slope,
                                            predictedLifetimes.lifeAtT0,
                               predictedLifetimes.T0);
    }
  }
}
logPredictedLifetimes= {       name     : "LogPredictedLifetime",
                        populate : // Calculate dataTable's column of logs of lifetime predictions
("LogPredictedLifetimes")
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.predictedLifetimes.length;
dataTableIndex++){
                  dataTable.logPredictedLifetimes[dataTableIndex]
        =Math.log2(dataTable.predictedLifetimes[dataTableIndex]);
    }
  }
}
fittingErrors        = {       name: "FittingErrors",
                      populate : // Calculate dataTable's column of fitting errors between lifetime data
and lifetime model ("fittingErrors")
  function calcFittingErrors(){
    for (dataTableIndex=0; dataTableIndex<dataTable.logPredictedLifetimes.length;
dataTableIndex++){
             dataTable.fittingErrors[dataTableIndex]
               = dataTable.predictedLifetimes[dataTableIndex] <
dataTable.lifetimeData[dataTableIndex]
                  ?
                  (dataTable.lifetimeData[dataTableIndex] -
dataTable.predictedLifetimes[dataTableIndex])
                        / dataTable.lifetimeData[dataTableIndex]
```

```
                        :
                        (dataTable.predictedLifetimes[dataTableIndex] -
dataTable.lifetimeData[dataTableIndex])
                          / dataTable.predictedLifetimes[dataTableIndex]
    }
  }
}
squaredFittingErrors = {       name : "SquaredFittingErrors",
                        SSR : "uninitialized",
                                                    populate : // Calculate dataTable's column of
squared fitting errors (squaredFittingErrors)
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.fittingErrors.length; dataTableIndex++){
      dataTable.squaredFittingErrors[dataTableIndex]
        =dataTable.fittingErrors[dataTableIndex]**2;
    }
  },                    calcSSR : // Calculate SSR
  function (){
    squaredFittingErrors.SSR=0;
    for (dataTableIndex=0; dataTableIndex<dataTable.squaredFittingErrors.length;
dataTableIndex++){
      squaredFittingErrors.SSR += dataTable.squaredFittingErrors[dataTableIndex];
    }
  }
}
predictedStartDates = {        name : "PredictedStartDates",
                       populate : // Calculate dataTable's column of start dates
("predictedStartDates")
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.predictedLifetimes.length;
dataTableIndex++){
      dataTable.predictedStartDates[dataTableIndex]
        = dataTable.endYear[dataTableIndex] - dataTable.predictedLifetimes[dataTableIndex];
    }
  }
}

let dataTable = {
  key                : [2012 , 2013 , 2014 , 2015 , 2016 , 2017 , 2018 , 2019 , 2020],
  endYear            : [2012 , 2013 , 2014 , 2015 , 2016 , 2017 , 2018 , 2019 , 2020],
  lifetimeData       : [3.379 ,3.289 ,3.256 ,3.363 ,3.579 ,3.571 ,3.760 ,3.861 ,3.636],
  logLifetimeData    : [], //to be initialized once
  predictedLifetimes  : [], //to be calculated by the regression process
  logPredictedLifetimes: [], //to be calculated by the regression process
  fittingErrors      : [], //to be calculated by the regression process
  squaredFittingErrors : [], //to be calculated by the regression process
  predictedStartDates  : []  //to be calculated by the regression process
}
logLifetimeData.populate(); //Calculate once as part of initialization.

function updateDataTableFromModelParams(){
```

```
   predictedLifetimes   .populate();
//alert("dataTable.predictedLifetimes="+dataTable.predictedLifetimes);
   logPredictedLifetimes.populate();
 //  alert("dataTable.logPredictedLifetimes="+dataTable.logPredictedLifetimes);
   fittingErrors        .populate();
   //   alert("dataTable.fittingErrors="+dataTable.fittingErrors);
   squaredFittingErrors .populate(); squaredFittingErrors.calcSSR();
     // alert("dataTable.squaredFittingErrors="+dataTable.squaredFittingErrors);
   predictedStartDates  .populate();
    //  alert("dataTable.predictedStartDates="+dataTable.predictedStartDates);
}
updateDataTableFromModelParams();

function fillInSSR(slope, lifeAtT0){
   predictedLifetimes.slope    = slope;
   predictedLifetimes.lifeAtT0 = lifeAtT0;
   updateDataTableFromModelParams();
   return({slope : slope, lifeAtT0 : lifeAtT0, SSR : squaredFittingErrors.SSR});
}

function searchLifeAtT0forSSRdip1pass(slope, lifeAtT0, lifeAtT0increment){
   let dataPointLlifeAtT0, dataPointMlifeAtT0, dataPointHlifeAtT0, dataPointTemp;
   dataPointLlifeAtT0 = fillInSSR(slope, lifeAtT0);
   dataPointMlifeAtT0 = fillInSSR(slope, lifeAtT0*=lifeAtT0increment)
   while(true){
     dataPointHlifeAtT0 = fillInSSR(slope, lifeAtT0*=lifeAtT0increment);
     if (dataPointLlifeAtT0.SSR < dataPointMlifeAtT0.SSR) {
             log("<hr><b>Error, no dip, possibly due to an unreasonable value for
slope:</b><br>dataPointLlifeAtT0.SSR < dataPointMlifeAtT0.SSR in
searchlifeAtT0forSSRdip1pass: slope="
                       +slope+", lifeAtT0increment="+lifeAtT0increment+",<br>dataPointLlifeAtT0
.lifeAtT0="+dataPointLlifeAtT0.lifeAtT0
                             +", dataPointLlifeAtT0
.SSR="+dataPointLlifeAtT0.SSR+"<br>dataPointMlifeAtT0.lifeAtT0="
                             +dataPointMlifeAtT0.lifeAtT0+",
dataPointMlifeAtT0.SSR="+dataPointMlifeAtT0.SSR);break;}
       else if (dataPointMlifeAtT0.SSR < dataPointHlifeAtT0.SSR) {break;} //The min SSR occurs
somewhere between L(ow) and H(igh) values of calcFittingErrors
       else {dataPointTemp        = dataPointLlifeAtT0;
                  dataPointLlifeAtT0   = dataPointMlifeAtT0;
            dataPointMlifeAtT0   = dataPointHlifeAtT0;
                        dataPointHlifeAtT0   = null;
                       }
   }
         // Next, enforce that on exit, dataTable contains data from the dip (not rejected data from
dataPointHlifeAtT0)    fillInSSR(slope, dataPointMlifeAtT0.lifeAtT0);
         return({dataPointLlifeAtT0 : dataPointLlifeAtT0, dataPointMlifeAtT0 : dataPointMlifeAtT0,
dataPointHlifeAtT0 : dataPointHlifeAtT0});
}

function searchLifeAtT0forMinSSRmultipass(slope, loBoundLifeAtT0){
```

```
  let lifeAtT0increment = lifeAtT0incrementFactor;   //if lifeAtT0increment is 2, and
lifeAtT0incrementFactorRefinement is 5,
                                                                    //then the updated
lifeAtT0increment is 1.2
  for (lifeAtT0increment ; lifeAtT0increment>lifeAtT0incrementFactorMin ;
lifeAtT0increment=1+(lifeAtT0increment-1)/lifeAtT0incrementFactorRefinement){
        loBoundLifeAtT0 = searchLifeAtT0forSSRdip1pass(slope, loBoundLifeAtT0,
lifeAtT0increment).dataPointLlifeAtT0.lifeAtT0;
  }
  let u = searchLifeAtT0forSSRdip1pass(slope, loBoundLifeAtT0, lifeAtT0increment); //u is set
to the three data points of the u-shaped dip
  log("<hr>Here is the region of lifeAtT0 giving lowest SSR for slope="+slope+":");
  log("For lifeAtT0="+u.dataPointLlifeAtT0.lifeAtT0+", SSR="+u.dataPointLlifeAtT0.SSR);
  log("For lifeAtT0="+u.dataPointMlifeAtT0.lifeAtT0+", SSR="+u.dataPointMlifeAtT0.SSR+"
<b>(best)</b>");
  log("For lifeAtT0="+u.dataPointHlifeAtT0.lifeAtT0+", SSR="+u.dataPointHlifeAtT0.SSR);
  return(u.dataPointMlifeAtT0);
}

function getLifeAtT0byDispatch(slope){
  if (lifeAtT0 === "Determined algorithmically")
    return searchLifeAtT0forMinSSRmultipass(slope, lifeAtT0min);
  else if (typeof lifeAtT0 === "number")
        return fillInSSR(slope, lifeAtT0);
  else alert("Error 101: lifeAtT0 === " + lifeAtT0 + ": bad value");
}

function searchSlopeforMinSSR(){
  let dataPointLslope;
  let dataPointMslope;
  let dataPointHslope;
  let nextSlope;
  dataPointLslope = getLifeAtT0byDispatch(0                    );
  dataPointMslope = getLifeAtT0byDispatch(minPosSlope          );
  dataPointHslope = getLifeAtT0byDispatch(minPosSlope*slopeIncrement);
  if (dataPointLslope.SSR < dataPointMslope.SSR) {
    log("Possibly an error.");
  };

  for (nextSlope = dataPointHslope.slope*slopeIncrement
        ; dataPointMslope.SSR > dataPointHslope.SSR   //";" is not a statement separator
here
        ; nextSlope *= slopeIncrement){
      dataPointLslope = dataPointMslope;
      dataPointMslope = dataPointHslope;
    dataPointHslope = getLifeAtT0byDispatch(nextSlope);
  }

  fillInSSR(dataPointMslope.slope, dataPointMslope.lifeAtT0); // Reset dataTable to dip
  log("<hr><hr><b>Summary: here is the region of best slope (that is, the slope with lowest
SSR):</b>");
```

```
  log("Slope just below the best slope: slope = "+dataPointLslope.slope+",    lifeAtT0 with lowest
SSR is "+dataPointLslope.lifeAtT0+" with SSR="+dataPointLslope.SSR);
  log('<span style="background-color: violet;");><b>Best slope: slope = ' +
dataPointMslope.slope + ", lifeAtT0 is " + dataPointMslope.lifeAtT0 + " and SSR=" +
dataPointMslope.SSR + " (lowest SSR found.)</span>");
  log(  '<span style="background-color: violet;"><b>'
     + "Equation of best fit curve is:        <b>"
          + "lifetime(endTime) = y = ["+dataPointMslope.slope+"*(x - " + T0 + ") + " +
dataPointMslope.lifeAtT0 + "]"
     + " / "
     + "[1 + " + dataPointMslope.slope + "]"
          + "</span>");
  for (let i=0; i<dataTable.endYear.length; i++){
    log(  '       <span style="background-color:
violet;"><b>'
       + "For end year " + dataTable.endYear[i] + ", ave. lifetime = " + dataTable.lifetimeData[i]
       + ", regressed model prediction = " + dataTable.predictedLifetimes[i]
          + "</span>"); };
  log("       Next line checks previous line:
predictions should be equal.");
  {let firstFutureYear = dataTable.endYear[dataTable.endYear.length-1]  // +1;
   for (let i=firstFutureYear ; i<=firstFutureYear+50 ; i++){
       log(  '       <span style="background-color:
violet;"><b>'
          + "For end year " + i + ", ave. lifetime = (data not present), regressed model prediction
= "
          + lifetimeFromFaildateAnyT0(i, dataPointMslope.slope, dataPointMslope.lifeAtT0, T0)
          + "</span>");
   }
  }
  log("Slope just above best slope: slope = "+dataPointHslope.slope+",    lifeAtT0 with lowest
SSR is "+dataPointHslope.lifeAtT0+" with SSR="+dataPointHslope.SSR);
  // return(dataPointMslope.slope); //not used, so why have it
}

function log(messageLine){
  document.getElementById("log").innerHTML+=messageLine+"<br>";
}

function lifetimeFromFaildateAnyT0(failDate, slope, lifeAtT0, yearOfT0) {
  return((slope*(failDate-yearOfT0)+lifeAtT0)/(1+slope));
}


</script>

</body>
</html>
```

Logistic

```
<!DOCTYPE html>
<html>
<head>
<title>KC Curve Fitting</title>
</head>
<body>

<h1>Data from SEER Nov 2022 Sub (1992-2020) Database - 20 Year Cause-Specific Survival Time of Kidney and Renal Pelvis Cancer Patients That Died in Years 2012-2020</h1>
<h2>Logistic Model with Survival Time Set to:    <kbd>const supremum = <span id="supremum">ERROR</span>;</kbd>
<br>(this should be set in the code to match the data)</h2>
<h3><i>Model update of 7/12/2024</i></h3>

<button onclick="document.getElementById('log').innerHTML='';
            searchtMidForMinSSR(steepnessMultiplier);">
        Click to find the logistic curve with the midpoint year and steepness yielding the best fit (lowest SSR)
</button>
<br><br>

<button onclick="document.getElementById('log').innerHTML='';
            searchSteepnessForMinSSR(parseFloat(prompt('Type year of midpoint:'), 10), steepnessMultiplier);">
        Click to find the logistic curve with the best fit steepness for a given midpoint year
</button>
<br><br>

<button onclick="document.getElementById('log').innerHTML='';
            log('SSR = ' + fillInSSR(parseFloat(prompt('Type value for steepness:'    ), 10),
                                parseFloat(prompt('Type value for midpoint year:'), 10)
                                                                ).SSR
                                        );">
        Click to input the steepness and midpoint year, and find the SSR
</button>
<br><br>

<button id="tMidStart"
                onclick="tMidStart=parseInt(prompt('What year would you like to search upward from?'));
                        document.getElementById('tMidStart').innerHTML
                                =   'Midpoint year search will now start from <mark><b>'
                                    + tMidStart
                                    + '</b></mark>. Consider changing it in the code. Click to try another value.'; ">
        Error 17
</button>
```

```
<p id="log"></p>

* Asterisk indicates suspected floating point roundoff error during steepness bisection. It is probably alright if steepnesses are closely spaced and middle SSR is lowest. If middle SSR equals another one, that actually was connected in one case to incorrect determination of the steepness with minimum SSR, probably due to another instance of roundoff error connected to a steepnessMultiplier being too close to 1.

<script>
const supremum = 20; //If the survival period for the data is 10 years, then the maximum average survival time is 10.
  document.getElementById("supremum").innerHTML = "<mark>"+supremum+"</mark>";
//Write the supremum prominently on the web page
let   tMidStart = 2015; //year to begin searching upward for midpoint of the logistic curve.
                  //Should undercut the midpoint, or it will lead to a non-termination condition.
  document.getElementById("tMidStart").innerHTML
    = "Midpoint search will start at year <mark><b>"+tMidStart+"</b></mark>. Click to change.";

const minPositiveSteepness = 0.000001; //0.000001 seems smaller than necessary. 0.0001 is probably plenty small.
const steepnessMultiplier=2; //1.01 led to longer execution times, as well as
                        //errors in finding the minimum for very small steepnesses,
                        //possibly due to getting stuck at false local minima
                                                        //caused by bumpiness from roundoff error due to large bisection   Epsilon=0.00001.
                                                        //2 is good because the initial steepnesses tested
                                                        //are 0, minPositiveSteepness and 2*minPositiveSteepness which are evenly spaced.
const minDeltaSSR = 0.00000001;
const bisectionEpsilon=0.0000001; //This turns out to matter in cases where steepness is close to zero.

predictedLifetimes   = {       name : "PredictedLifetimes",
                       steepness : 1,            //initial guess
                           tMid : 2025,         //initial guess
                                                        populate : // Calculate dataTable's column of lifetime predictions from fail dates (predictedLifetimes)
  function (){
          if (!isFinite(predictedLifetimes.steepness)||!isFinite(predictedLifetimes.tMid))
            alert("Error in predictedLifetimes.populate(): non-numeric arg(s)!"); //make sure they are int or float
          for (dataTableIndex=0; dataTableIndex<dataTable.endYear.length; dataTableIndex++){
       dataTable.predictedLifetimes[dataTableIndex]
         =lifetimeFromFaildate(dataTable.endYear[dataTableIndex],
                                  predictedLifetimes.steepness,
                            predictedLifetimes.tMid,
                                                                  supremum);
    }
//if (!isFinite(predictedLifetimes.steepness)) alert(dataTable.predictedLifetimes); //reports actual numbers. Scary.
```

```
  }
}

fittingErrors       = {      name : "FittingErrors",
                      populate : // Calculate dataTable's column of fitting errors between lifetime data
and lifetime model ("fittingErrors")
  function calcFittingErrors(){
    for (dataTableIndex=0; dataTableIndex<dataTable.predictedLifetimes.length;
dataTableIndex++){
            dataTable.fittingErrors[dataTableIndex] =
Math.abs(dataTable.predictedLifetimes[dataTableIndex] -
dataTable.lifetimeData[dataTableIndex]);
//if (dataTableIndex==0) alert("dataTable.fittingErrors[0] is
"+dataTable.fittingErrors[dataTableIndex] );
    }
  }
}
squaredFittingErrors = {       name : "SquaredFittingErrors",
                          SSR : "uninitialized",
                                                  populate : // Calculate dataTable's column of
squared fitting errors (squaredFittingErrors)
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.fittingErrors.length; dataTableIndex++){
      dataTable.squaredFittingErrors[dataTableIndex]
        =dataTable.fittingErrors[dataTableIndex]**2;
    }
  },                    calcSSR : // Calculate SSR
  function (){
    squaredFittingErrors.SSR=0;
    for (dataTableIndex=0; dataTableIndex<dataTable.squaredFittingErrors.length;
dataTableIndex++){
                    squaredFittingErrors.SSR += dataTable.squaredFittingErrors[dataTableIndex];
    }
  }
}
predictedStartDates = {        name : "PredictedStartDates",
                       populate : // Calculate dataTable's column of start dates
("predictedStartDates")
  function (){
    for (dataTableIndex=0; dataTableIndex<dataTable.predictedLifetimes.length;
dataTableIndex++){
      dataTable.predictedStartDates[dataTableIndex]
        = dataTable.endYear[dataTableIndex] - dataTable.predictedLifetimes[dataTableIndex];
    }
  }
}

let dataTable = {
  key              : [2012 ,2013 ,2014 ,2015 ,2016 ,2017 ,2018 ,2019 ,2020],
  endYear            : [2012 ,2013 ,2014 ,2015 ,2016 ,2017 ,2018 ,2019 ,2020],
  lifetimeData       : [3.379 ,3.289 ,3.256 ,3.363 ,3.579 ,3.571 ,3.760 ,3.861 ,3.636],
```

```
  predictedLifetimes   : [], //to be calculated by the regression process
  fittingErrors        : [], //to be calculated by the regression process
  squaredFittingErrors : [], //to be calculated by the regression process
  predictedStartDates  : []  //to be calculated by the regression process
}
//logLifetimeData.populate(); //Calculate once as part of initialization.

function updateDataTableFromModelParams(){
  predictedLifetimes   .populate();
  fittingErrors        .populate();
//alert("dataTable.fittingErrors is "+dataTable.fittingErrors);
  squaredFittingErrors .populate(); squaredFittingErrors.calcSSR();
  predictedStartDates  .populate();
}
updateDataTableFromModelParams();

function fillInSSR(steepness, tMid){
//alert(steepness + " " + tMid);
  if (!isFinite(tMid)||!isFinite(steepness)) alert("Error in fillInSSR: steepness,
tMid="+steepness+","+tMid);
  predictedLifetimes.steepness = steepness;
  predictedLifetimes.tMid = tMid;
  updateDataTableFromModelParams();
  return({steepness : steepness, tMid : tMid, SSR : squaredFittingErrors.SSR});
}
//alert("fillInSSR(1, 2040).SSR returns "+fillInSSR(1, 2040).SSR);

//returns a string: "positive",          "negative",            "zero or near zero",
//                  "positive edge case", "negative edge case" or "anomaly".
function getSteepnessSign(tMid){
  let SSR0             =fillInSSR(0                  , tMid).SSR; //SSR for zero     steepness
  let SSRminPosSteepness=fillInSSR( minPositiveSteepness, tMid).SSR; //SSR for positive
steepness nearest 0
  let SSRmaxNegSteepness=fillInSSR(-minPositiveSteepness, tMid).SSR; //SSR for negative
steepness nearest 0
//alert("in getSteepnessSign, SSRs: 0="+SSR0+" SSRminPosSteepness="+
//    SSRminPosSteepness+" SSRmaxNegSteepness="+SSRmaxNegSteepness);
  if      (SSRminPosSteepness< SSR0) return "positive";
  else if (SSRmaxNegSteepness< SSR0) return "negative";
  else if (SSRminPosSteepness> SSR0 && SSRmaxNegSteepness> SSR0)
      return "zero or near zero";
  else if (SSRminPosSteepness> SSR0 && SSRmaxNegSteepness==SSR0)
      return "negative edge case";
  else if (SSRminPosSteepness==SSR0 && SSRmaxNegSteepness> SSR0)
      return "positive edge case";
  else return "anomaly";
}
function searchSteepnessForMinSSR(tMid, steepnessMultiplier){
  if (!isFinite(tMid)||!isFinite(steepnessMultiplier)) alert("Error in searchSteepnessForMinSSR:
non-numeric arg(s)");
```

```
  //Initialize for steepnesses by getting ready to crawl upward or downward from 0, unless 0 is
already optimal
  let dataPointLsteepness, dataPointMsteepness, dataPointHsteepness; //L,M,H for low, middle,
high absolute value.
  let dataPointTemp;
  let dataPointLMsteepness, dataPointMHsteepness; //Midway between L&M, M&H, used to
focus in on the min.
  let steepness=getSteepnessSign(tMid); //Make it more precise later.
  if     (steepness=="positive") {dataPointLsteepness = fillInSSR(steepness= 0, tMid);
                                  dataPointMsteepness = fillInSSR(steepness= minPositiveSteepness,
tMid);
                                                                                  dataPointHsteepness =
fillInSSR(steepness= minPositiveSteepness*steepnessMultiplier, tMid);
                                                                                }
  else if (steepness=="negative") {dataPointLsteepness = fillInSSR(steepness= 0, tMid);
                                  dataPointMsteepness = fillInSSR(steepness=-minPositiveSteepness,
tMid);
                                                                                  dataPointHsteepness =
fillInSSR(steepness=-minPositiveSteepness*steepnessMultiplier, tMid);
                                                                                }
  else if (steepness=="zero or near zero")
                                 {dataPointLsteepness = fillInSSR(steepness=-minPositiveSteepness,
tMid);
                                                                                  dataPointMsteepness =
fillInSSR(steepness=0, tMid);
                                                                                       dataPointHsteepness =
fillInSSR(steepness= minPositiveSteepness, tMid);
                                                                                }
  else alert("Unhandled return value from getSteepnessSign: "+steepness);
  if (dataPointLsteepness.SSR < dataPointMsteepness.SSR) {alert("Error #3"); return "Error
#3";}
  //Crawl upward or downward searching for a steepness interval containing the minimum SSR
  while((dataPointMsteepness.SSR>=dataPointHsteepness.SSR)){ //exit when min SSR occurs
between steepnesses L and H
  //alert("starting while");
          if ((dataPointLsteepness.SSR == dataPointMsteepness.SSR)
             &&
                  (dataPointMsteepness.SSR == dataPointHsteepness.SSR))
                 {log("<b>SSR appears to be asymptoting as steepness magnitude increases for"
+
                      ": year="      + tMid      +
                           ", steepness=" + steepness +
                           ", SSR="       + dataPointHsteepness.SSR + "</b><br>");
        break;
                 }
          dataPointLsteepness = dataPointMsteepness;
          dataPointMsteepness = dataPointHsteepness;
    dataPointHsteepness = fillInSSR(steepness*=steepnessMultiplier, tMid);
  }
/*
alert( dataPointLsteepness.steepness
```

```
            +","
            +dataPointMsteepness.steepness
            +","
            +dataPointHsteepness.steepness);
alert( dataPointLsteepness.SSR
            +","
            +dataPointMsteepness.SSR
            +","
            +dataPointHsteepness.SSR);
*/
//alert("before for");
  //Subdivide steepness interval containing minimum SSR until a sufficiently accurate best
steepness is found
  for (var deltaSSR=dataPointLsteepness.SSR-dataPointMsteepness.SSR;
       !(deltaSSR<minDeltaSSR)                              ; //2/15/24: unlikely to trigger before the
final else's break
                  deltaSSR    =dataPointLsteepness.SSR-dataPointMsteepness.SSR
            ){
      //alert("deltaSSR is "+deltaSSR+", !(deltaSSR<minDeltaSSR) is
"+!(deltaSSR<minDeltaSSR));
      dataPointLMsteepness =
fillInSSR((dataPointLsteepness.steepness+dataPointMsteepness.steepness)/2, tMid);
      dataPointMHsteepness =
fillInSSR((dataPointMsteepness.steepness+dataPointHsteepness.steepness)/2, tMid);

//alert(dataPointLsteepness.SSR+","+dataPointLMsteepness.SSR+","+dataPointMsteepness.S
SR+","
      //      +dataPointMHsteepness.SSR+","+dataPointHsteepness.SSR);
      if (  dataPointLsteepness.SSR>dataPointLMsteepness.SSR &&
dataPointLMsteepness.SSR>dataPointMsteepness.SSR
                  && dataPointMsteepness.SSR<=dataPointMHsteepness.SSR &&
dataPointMHsteepness.SSR<dataPointHsteepness.SSR)
            {dataPointLsteepness=dataPointLMsteepness;    //M  is lowest, so trim L and H
                  dataPointHsteepness=dataPointMHsteepness;}
      else if
            (  dataPointLsteepness.SSR>dataPointLMsteepness.SSR &&
dataPointLMsteepness.SSR>dataPointMsteepness.SSR
            && dataPointMsteepness.SSR>dataPointMHsteepness.SSR &&
dataPointMHsteepness.SSR<dataPointHsteepness.SSR)
            {dataPointLsteepness=dataPointMsteepness ;    //MH is lowest, so trim L and LM
                  dataPointMsteepness=dataPointMHsteepness;}
      else if
            (  dataPointLsteepness.SSR>dataPointLMsteepness.SSR &&
dataPointLMsteepness.SSR<dataPointMsteepness.SSR
            && dataPointMsteepness.SSR<dataPointMHsteepness.SSR &&
dataPointMHsteepness.SSR<dataPointHsteepness.SSR)
            {dataPointHsteepness=dataPointMsteepness ;    //LM is lowest, so trim H and MH
                  dataPointMsteepness=dataPointLMsteepness;}
      else{//alert("Error in searchSteepnessForMinSSR; anomalous SSR pattern "+tMid);
```

```
//alert(dataPointLsteepness.SSR+","+dataPointLMsteepness.SSR+","+dataPointMsteepness.S
SR+","
          //      +dataPointMHsteepness.SSR+","+dataPointHsteepness.SSR);

//alert(dataPointLsteepness.steepness+","+dataPointLMsteepness.steepness+","+dataPointMst
eepness.steepness+","
          //      +dataPointMHsteepness.steepness+","+dataPointHsteepness.steepness);
                    log("* "); break; //The point here is to keep looping until floating point roundoff
error starts creating anomalies
        }
  }
  //print out region of steepness with lowest SSR
  log("For midpoint year " + tMid + ":<br>"
     + "steepness " + dataPointLsteepness.steepness + " has SSR " +
dataPointLsteepness.SSR + "<br>"
          + "steepness " + dataPointMsteepness.steepness + " has SSR " +
dataPointMsteepness.SSR + "<br>"
          + "steepness " + dataPointHsteepness.steepness + " has SSR " +
dataPointHsteepness.SSR + "<hr>"
          );
  //return data steepness with lowest SSR
  fillInSSR(dataPointMsteepness.steepness, dataPointMsteepness.tMid); //Make dataTable
reflect the dip, not H after the dip
  return(dataPointMsteepness);
}

function searchtMidForMinSSR(steepnessMultiplier){
  if (!isFinite(steepnessMultiplier)) alert("Error in searchtMidForMinSSR: steepnessMultiplier is
non-numeric!");
  let nexttMid = tMidStart;
  let dataPointLtMid = searchSteepnessForMinSSR(nexttMid  , steepnessMultiplier);
  let dataPointMtMid = searchSteepnessForMinSSR(nexttMid+1, steepnessMultiplier); //search
one year at a time
  let dataPointHtMid = searchSteepnessForMinSSR(nexttMid+2, steepnessMultiplier);
  if ((dataPointLtMid.SSR < dataPointMtMid.SSR)) { //Why the steepness check?
    {log("<b>Warning: no improvement in SSR detected. Try giving start year tMidStart a
different value.</b><br>"); return;}
  };
  for (  nexttMid=dataPointHtMid.tMid+1 ;
       dataPointMtMid.SSR >= dataPointHtMid.SSR;
                  nexttMid+=1){
    //alert(nexttMid);
          if (  (dataPointLtMid.SSR==dataPointMtMid.SSR)
              &&
                        (dataPointMtMid.SSR==dataPointLtMid.SSR)){
       log("<b>SSR appears to be asymptotic with increasing midpoint year, so ending the
search.</b></br>");
       break;
    }
    dataPointLtMid = dataPointMtMid;
```

```
      dataPointMtMid = dataPointHtMid;
      dataPointHtMid = searchSteepnessForMinSSR(nexttMid, steepnessMultiplier);
      //log("For midpoint year "+dataPointLtMid.tMid+", steepness with lowest SSR is "
            //    +dataPointLtMid.steepness+" with SSR "+dataPointLtMid.SSR);
  }
  fillInSSR(dataPointMtMid.steepness, dataPointMtMid.tMid); //Make dataTable reflect the dip,
not H after the dip.
  log("<b>Summary: here is the region of best tMid (that is, the midpoint time with lowest SSR)
found:</b><br>");
  log("Midpoint just below the best one: midpoint year = "+dataPointLtMid.tMid+", steepness
with lowest SSR is "+dataPointLtMid.steepness+" with SSR "
      +dataPointLtMid.SSR+"<br>");
  log('<span style="background-color: yellow;"><b>Best midpoint year: midpoint = '
      + dataPointMtMid.tMid
                  + ", steepness with lowest SSR is "
                  + dataPointMtMid.steepness
                  + " and SSR "
                  + dataPointMtMid.SSR
                  + "<br>    This is the best midpoint time and steepness
with lowest SSR (unless asymptoting)!</b></span><br>"
          );
  log(  '<span style="background-color: yellow;"><b>'
     + "Equation of best fit curve is:        <b>"
          + "x = ln(y)/" + dataPointMtMid.steepness + " + y + " + dataPointMtMid.tMid
               + " - ln(" + supremum + " - y)/" + dataPointMtMid.steepness
          + "         where x is the
INdependent variable despite the form of the equation."
          + "</span><br>");
  for (let i=0 ; i<dataTable.endYear.length ; i++){
    log(  '       <span style="background-color:
yellow;"><b>'
       + "For end year " + dataTable.endYear[i] + ", ave. lifetime = " + dataTable.lifetimeData[i]
       + ", regressed model prediction = " + dataTable.predictedLifetimes[i]
            + "</span><br>"); };
  log("       Next line checks previous line:
predictions should be equal.<br>");
  {let firstFutureYear = dataTable.endYear[dataTable.endYear.length-1];
   for (let i=firstFutureYear ; i<=firstFutureYear+50 ; i++){
      log(  '       <span style="background-color:
yellow;"><b>'
          + "For end year " + i + ", ave. lifetime = (data not present), regressed model prediction
= "
          + lifetimeFromFaildate(i, dataPointMtMid.steepness, dataPointMtMid.tMid, supremum)
          + "</span><br>");
   }
  }
  log("Midpoint just above the best one: midpoint year = "+dataPointHtMid.tMid+", steepness
with lowest SSR is "+dataPointHtMid.steepness+" with SSR "
      +dataPointHtMid.SSR+"<hr>");
}
```

```
function log(messageLine){
   document.getElementById("log").innerHTML+=messageLine+"";
}

//alert(Math.sign(-7));

// *** Use bisection method ***
function lifetimeFromFaildate(failDate, steepness, tMid, supremum) {
  const envelope=bisectionEpsilon; //0.0000001 worked, while 0.00001 led to noticeable issues
  var loBound=0, hiBound=supremum, guessedLife=(hiBound+loBound)/2;
  if (!isFinite(failDate)||!isFinite(steepness)||!isFinite(tMid)) alert("Error in lifetimeFromFaildate,
nonnumeric arg(s)");
  if (steepness==0) return(supremum/2); //Special treatment needed since the general formula
                                        //used in the loop is undefined for steepness 0
  else
     while ((hiBound-loBound)>envelope){
       ( Math.log(guessedLife)/steepness + guessedLife + tMid - Math.log(supremum -
guessedLife)/steepness
                  <
          failDate
                      ==
                      steepness>0
              )
       ? loBound=guessedLife
       : hiBound=guessedLife;
       guessedLife=(hiBound+loBound)/2;
     }
  return guessedLife; //Has converged on the answer
}
//alert(lifetimeFromFaildate(2036, -.01, 2031,10));

//alert("Javascript code loaded");

</script>
</body>
</html>
```

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