

# Healthcare Industry Adverse Disruptors Quantification 2016-2020

Hawkeye Solutions

THE University of Iowa

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## *Executive Summary*

To help a healthcare insurance company prepare and manage the unexpected and substantial cost, we identify and quantify the U.S. healthcare insurance disruptors within a five year horizon. In this report, we focus on three possible and pricey factors: chronic diseases, specialty drugs, and pandemics.

In the first part, we predict the number of people with chronic conditions in the next five years and calculate the healthcare cost for these people in each year. We find that the healthcare cost will increase by more than 1% every year, and the total healthcare spending by people with chronic conditions will increase by more than 53 billion dollars. In conclusion, chronic disease is a potential disruptor in the next five years, because of the growing population with chronic conditions.

In the specialty drugs chapter, we firstly predict the total cost of the best-selling specialty drugs from 2016 to 2020, and we show the predicted cost of the specialty drugs in each year. After this, we predict the total cost of newly approved specialty drugs and potential specialty drugs that will be approved in the next five years. Driven by specialty drugs with treatments for hepatitis C, rheumatoid arthritis and cancer, the cost of specialty drugs will keep soaring in the next five years. We find that these new drugs will be a disruptor for the insurers as much as 130 billion dollars. Although biosimilar product is expected to provide the insurers a relief from the soaring spending, this story can only happen after the original biologic drug loses its patent.

In the last part, we focus on the pandemic with high fatality and infection rate. We construct a stochastic SIRD model to simulate the outbreak pattern and calculate the expected potential cost. We find that the outbreak of this type pandemic will create a substantial cost in the outbreak period, which will be big shock to company's liquidity

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## ***1. Chronic Diseases***

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## ***1.1. Purpose and Background***

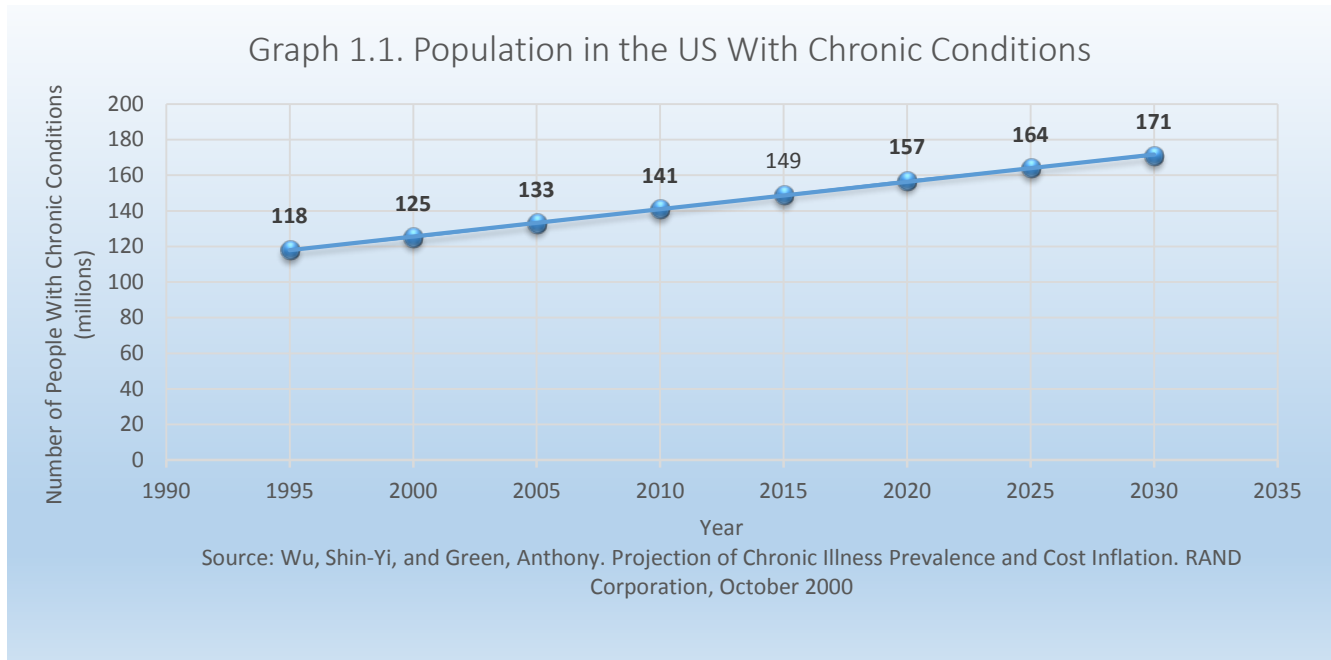
Chronic diseases, such as cancer, obesity and heart disease, are common in the US. These diseases are costly and lasting, at least, three months. With chronic illness population growth, the total healthcare coverage for chronic diseases is increasing rapidly. People with chronic conditions (CC) usually spend much more in healthcare. So if the number of people with chronic conditions becomes larger, our healthcare cost will increase significantly. Since we have the projection of population with chronic conditions (Wu & Green, 2000) in the US, we assumed a linear growth of population in every five years. Basing on the research (Gerteis, et al., 2014) about different numbers of chronic conditions, we divided our projected population into different groups. Considering that the research also provided the healthcare cost are varied by a number of chronic conditions, we calculated the cost for each group and the total cost for the next five years. By using growth rate, we determined the trend of our healthcare cost for people with chronic conditions.

## ***1.2. Data Source***

We used chronic disease data from the Agency for Healthcare Research and Quality (AHRQ). Also, we analyzed historical data from Centers of Medicare & Medicaid Services (CMS), because most people with multiple chronic conditions are Medicare beneficiaries. Since we have the projection of the number of people with chronic conditions and AHRQ provided the percentage of people with a different number of chronic conditions including zero, we recalculate the percentage among people who have at least one chronic condition by the number of chronic conditions. Moreover, CMS only provides data in Medicare beneficiaries, so we only analyzed the average cost in different years, since the cost of treatments by the number chronic conditions are relatively stable in different age groups.

### 1.3. Model

Firstly, we used the projected number of people with chronic conditions. This projection included numbers in the next 15 years.

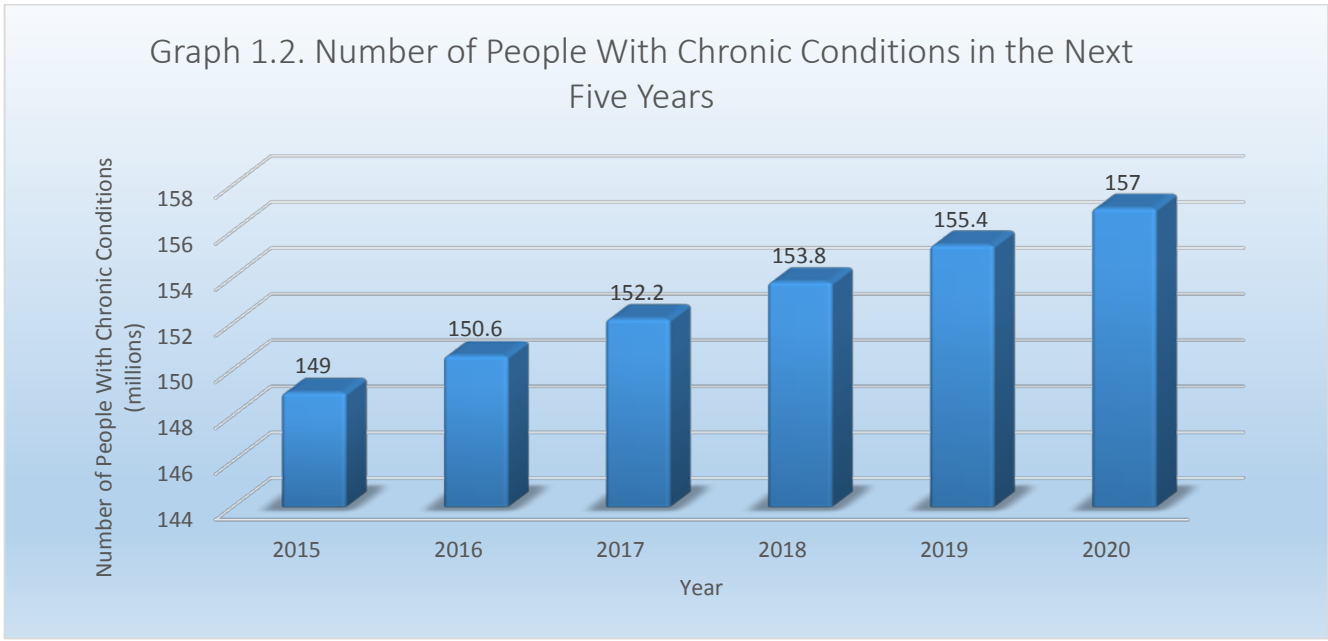


From the graph, we can see that the projection is almost linear growth. Also, we used linear regression, and the linear equation is

$$Y = -2950.67 + 1.5381X$$

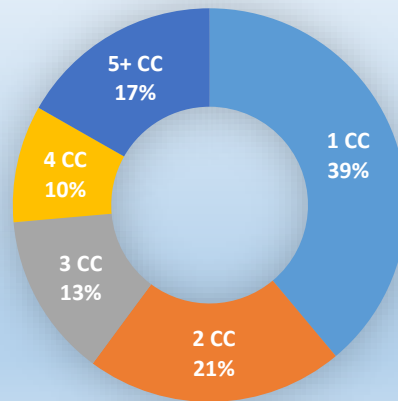
Y represents the number of people with chronic conditions, and X represents the year. Then we tested it by using mean square error (MSE) and mean absolute deviation (MAD). MSE is 0.1845 and MAD is 0.3512, so the error is relatively small.

Thus, we used the linear equation to predict the population of chronic diseases in the next five years. The numbers of American affected by chronic conditions during the next five years are in the graph below.



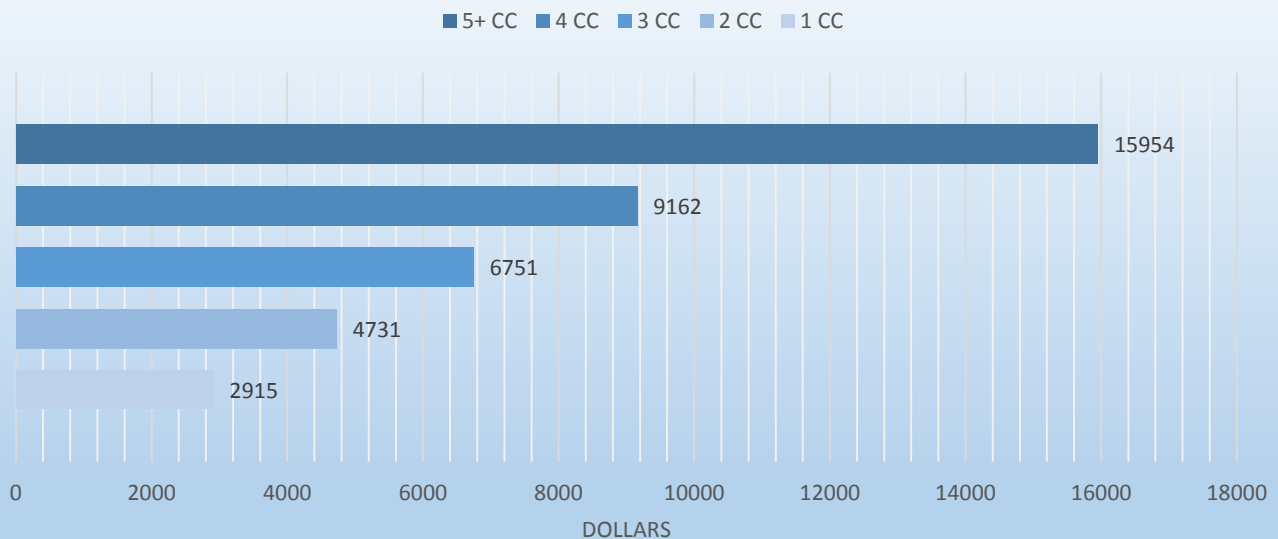
Then, we divided the population into five different groups basing on the number of chronic conditions in every year. From historical data (Chronic Conditions among Medicare Beneficiaries, Chart Book, 2011) (Chronic Conditions among Medicare Beneficiaries, Chart Book, 2012) (Chronic Conditions among Medicare Beneficiaries, Chart Book, 2014), we find that the average annual cost for the treatments of chronic diseases remains stable. Also, percentage of people with different chronic conditions is relatively stable. Moreover, most people with multiple chronic conditions are in the Medicare. So we assumed that the percentage of people with different number chronic conditions is same in the next five years, and average healthcare spending per person by the number of chronic conditions is constant. Then we had the distribution of the population according to Gerteis et al.:

Graph 1.3. Percentage of People With Chronic Conditions, by Number of Chronic Conditions



Since healthcare spending varies from group to group, we used different average cost for each group:

Graph 1.4. Health Cost Per Person, by Number of Chronic Conditions



SOURCES: GERTEIS J, IZRAEL D, DEITZ D, LEROY L, RICCIARDI R, MILLER T, BASU J. MULTIPLE CHRONIC CONDITIONS CHARTBOOK. AHRQ PUBLICATIONS NO, Q14-0038. ROCKVILLE, MD: AGENCY FOR HEALTHCARE RESEARCH AND QUALITY. APRIL 2014.

Finally, we used the total cost model

$$\text{Total Cost in each year} = \sum_{i=1}^4 C_i \times P_i + C_5 \times (P - \sum_{i=1}^4 P_i)$$



$C_i(1 \leq i \leq 4)$  represent the average healthcare cost per person with  $i$  chronic conditions,  $C_5$  represents the average cost per person with more than or equal five chronic conditions. We denote  $P$  by the total number of people with chronic conditions and  $P_i$  by the number of people with  $i$  chronic conditions. Using different average cost in a group increased our accuracy. For example, although the number of people with more than or equal to five chronic conditions is not very high, its average cost is the highest. So it is more precise by calculating costs by groups separately.

## 1.4. Results

Using the model above, we made the table for the healthcare costs in the next five years.

*Table 1.1. Projected total healthcare spending (in billion) by people with chronic conditions*

	2015	2016	2017	2018	2019	2020
<b>1cc</b>	169.7	171.52	173.35	175.17	176.99	178.81
<b>2cc</b>	149.98	151.59	153.2	154.81	156.42	158.04
<b>3cc</b>	136.2	137.66	139.12	140.58	142.05	143.51
<b>4cc</b>	132.02	133.44	134.86	136.28	137.7	139.11
<b>5+cc</b>	400.02	404.32	408.61	412.91	417.2	421.5
<b>Total</b>	987.93	998.54	1009.14	1019.75	1030.36	1040.97

From the table, we can see that our total healthcare costs increase by 53.04 billion dollars from 2015 to 2020. The growth rate is stable, but the cost in 2015 is large, so the difference is significant. We find that chronic disease is our disruptor because increasing number of people with chronic conditions. Although people with more than five chronic conditions are the least, the healthcare spending per person is much larger than other groups. So we can conclude that cost by people with more than five chronic conditions will occupy the largest part of healthcare spending in chronic diseases. Considering our projected growth rate, we notice that it is slightly decreasing, which means the healthcare cost by people with chronic conditions may remain stable in the future. However, during the next five years, it will increase rapidly. Because healthcare treatments for people with chronic conditions include inpatient services, outpatient services, physician services and pharmaceuticals, increasing the number of people with chronic conditions will affect these four aspects at the same time.

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## ***2. Specialty Drugs***

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## ***2.1. Background***

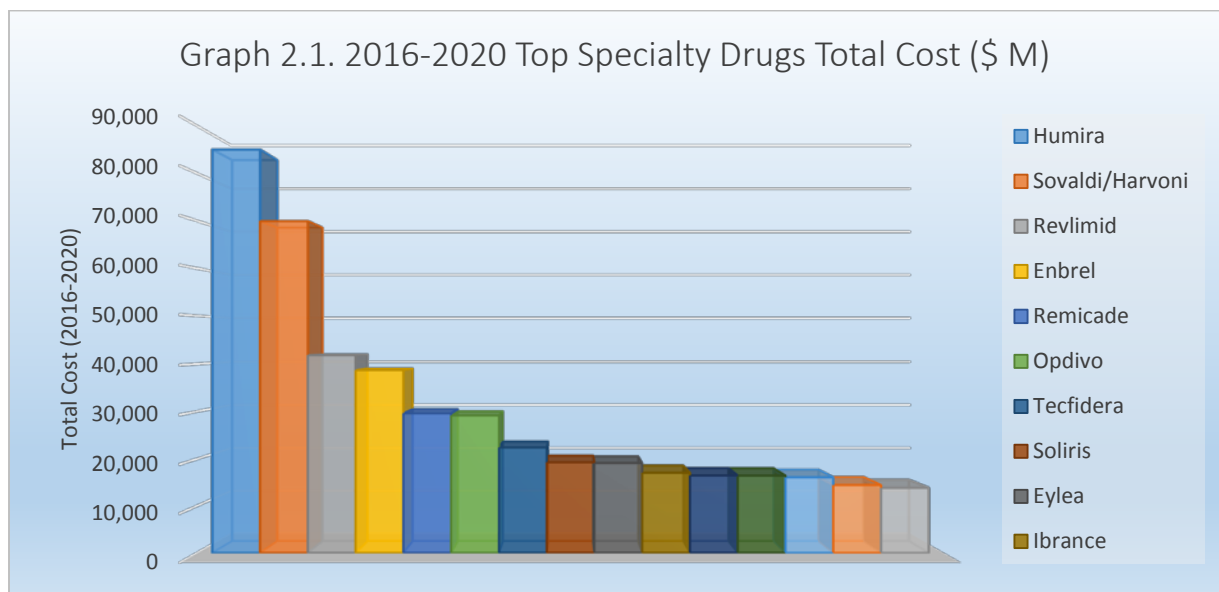
There was a huge surprise increase of healthcare pharmacy spending led by drugs with the treatment for Hepatitis C in 2013 and 2014 (Scripts, 2016). Specialty drugs used to treat complex, chronic and often costly conditions approved by the U.S. Food and Drug Administration (FDA) in the past two years and the future five years are expected to bring a large cost to patients and insurers. According to CVS Caremark, spending on specialty drugs is expected to reach \$400 billion by 2020 — or roughly 9 percent of the nation's projected total health care expenditures (Bill Hogan, 2015). In the next five years, the spending on specialty drugs will keep increasing and is predicted to reach 50% of total pharmacy spend by 2018 and maintain a 17% growth rate afterward (PwC, 2015). Therefore, to keep a close eye on specialty drugs is significant for the management of future disruptors.

## ***2.2. Data and Methodology***

We used the total sale data from large companies to approximate the specialty drugs cost. We also predicted the cost trend according to companies' sales trend. Sales data and prediction were collected from (DrugAnalyst, 2016). In order to locate the most expensive drugs and the most expected drugs, we researched online and read drug sales reports from pharmacy companies. For specific drugs, we researched and analyzed population of user and payment per patient per year to estimate specialty drug cost.

## 2.3. Top Specialty Drugs 2016-2020

Some specialty drugs for cholesterol therapies have been approved by FDA. They are expected to become one of the top sale drugs in the history as the maintenance drugs PCSK9 with a huge population as well as the high cost, and will be even much higher than drugs for Hepatitis C treatments (PwC, 2015). The FDA has only recently approved Amgen's next-gen cholesterol fighter, Repatha. This is one of the new cholesterol-lowering drugs, PCSK9 inhibitors. Given that a one-year course will cost \$14,100, Repatha is expected to generate \$2 billion by 2020 (Ishmael, 2015). According to the research and development pattern of FDA and the pipelines of pharmacy companies, some other cancer, rheumatoid arthritis and multiple sclerosis specialty drugs with similar cost are predicted to reach the market in five years. We predicted the top specialty drugs in each of the next five years and showed the total cost in Graph 2.1 to give you a clear view of future drug cost.



Source: Data are analyzed from (DrugAnalyst, 2016) (Patrick, 2016) (Nisen, 2016)

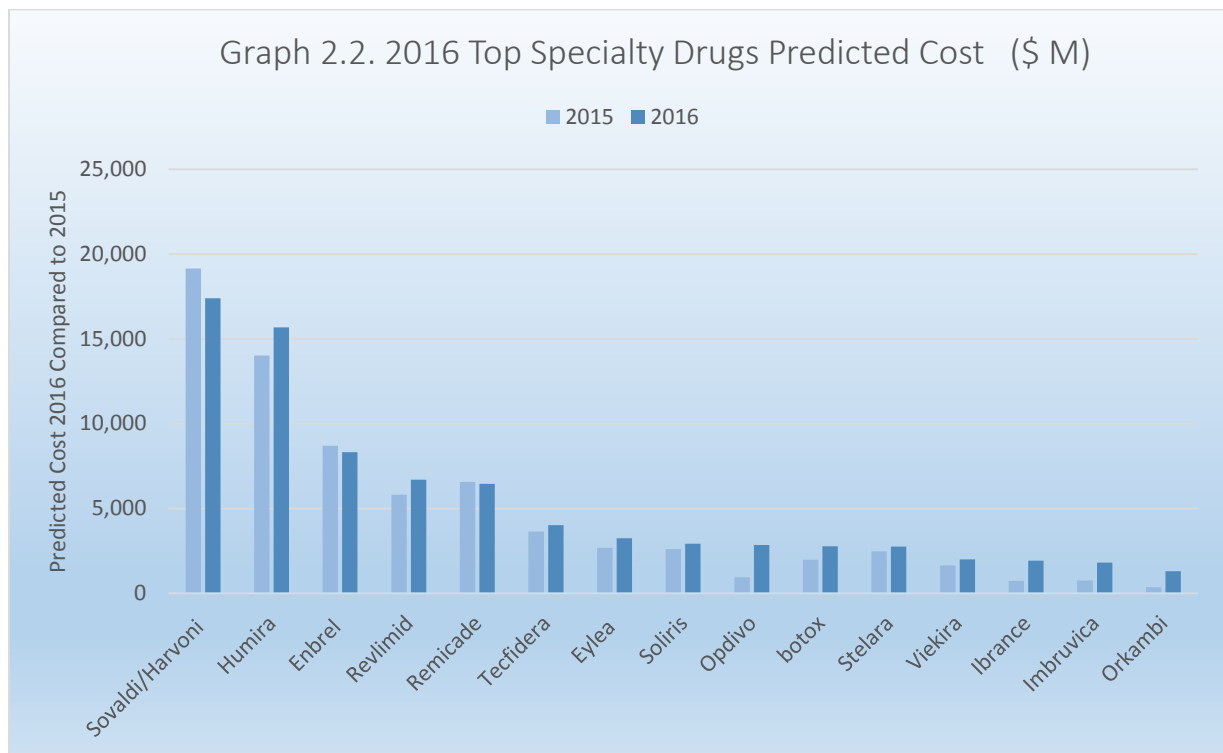
**Table 2.1. 2016-2020 Top Specialty Drugs (\$ M)**

<b>Drug</b>	<b>Indication</b>	<b>Company</b>	<b>Patent Expiry</b>	<b>Total Cost (2016-2020)</b>
Humira	Rheumatoid Arthritis	AbbVie	31-Dec-16	84,985
Sovaldi/Harvoni	Hepatitis C	Gilead		69,930
Revlimid	Multiple Myeloma	CELG	04-Oct-19	41,841
Enbrel	Rheumatoid Arthritis	Amgen,Pfizer	01-Apr-29	38,696
Remicade	Rheumatoid Arthritis	JOHNSON & JOHNSON	04-Sep-18	29,625
Opdivo	Non small cell lung cancer	Bristol		29,162
Tecfidera	Multiple Sclerosis	Biogen	29-Oct-19	22,420
Soliris	Paroxysmal Nocturnal Hemoglobinuria	Alexion	16-Mar-21	19,293
Eylea	AMD	Regeneron	22-May-20	19,126
Ibrance	Breast Cancer	Pfizer		17,072
botox	Frown Lines	Allergan		16,487
Imbruvica	Lymphocytic Leukaemia	AbbVie		16,463
Stelara	Psoriasis	JOHNSON & JOHNSON	01-Aug-21	16,107
Orkambi	Cystic Fibrosis	Vertex		14,450
TAF/Genvoya	HIV	Gilead		13,854

### 2.3.1. Year 2016

Specialty drugs including drugs for the treatment of high blood cholesterol, cancer, rheumatic diseases, and hematology will be approved by FDA in 2016 (PwC, 2015), and expected to bring a high cost to insurers. With a high cost per patient as well as the high population of patients, the total cost cost of drug for treatment of Hepatitis C, Sovaldi and Harvoni, will be the largest in 2016.

Hepatitis C drug, Vieira Pak with a complex regimen (a patient has to take multiple pills per day), is facing a new lower cost competitor. Zepatier, with \$54,600 per treatment (Fixhepc, 2016), was approved in January 2016. Actually, even if all the patients choose Zepatier, there would still be as much as \$2 billion cost for the very high population with Hepatitis C. In addition, there are more Hepatitis C therapies are still in the pharmacy pipeline, so insurers still need to pay a high attention to Hepatitis C drugs.

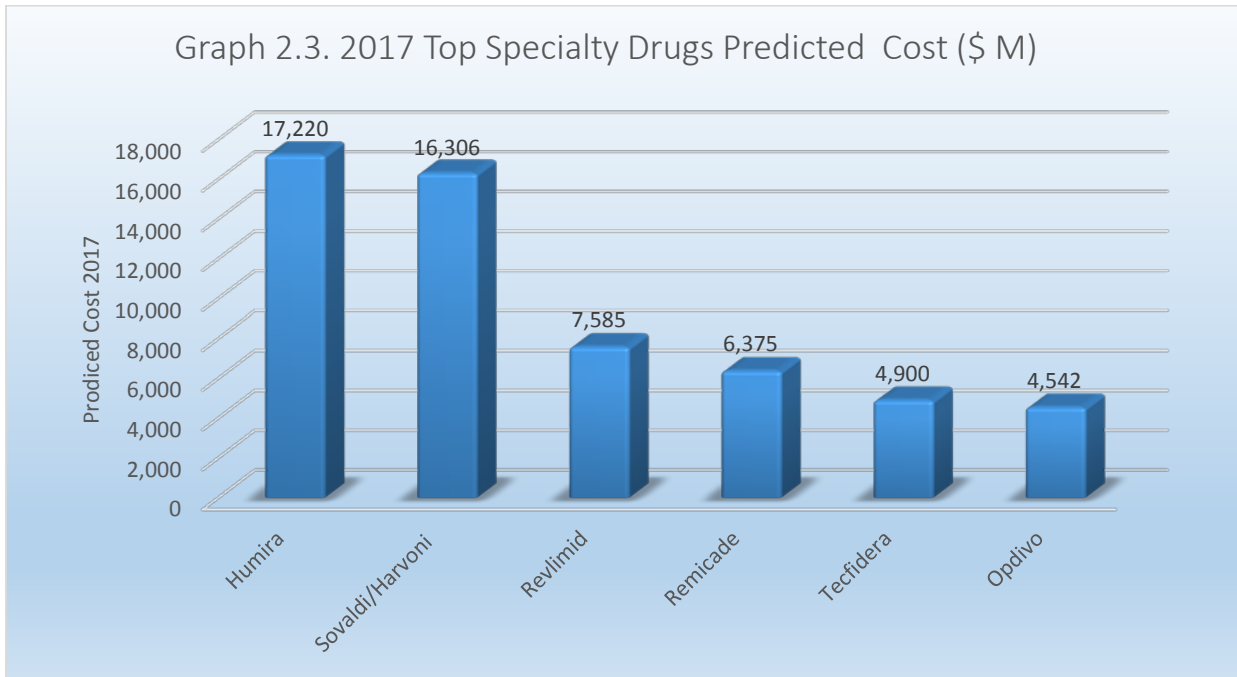


Source: Data are analyzed from (DrugAnalyst, 2016) (Patrick, 2016) (Nisen, 2016)

*Table 2.2. 2016 Top Specialty Drugs (\$ M)*

<b>Drug</b>	<b>Indication</b>	<b>Company</b>	<b>Patent Expiry</b>	<b>2015</b>	<b>2016</b>
Sovaldi/Harvoni	Hepatitis C	Gilead		19,140	17,389
Humira	Rheumatoid Arthritis	AbbVie	31-Dec-16	14,014	15,682
Enbrel	Rheumatoid Arthritis	Amgen,Pfizer	01-Apr-29	8,697	8,313
Revlimid	Multiple Myeloma	CELG	04-Oct-19	5,801	6,699
Remicade	Rheumatoid Arthritis	JOHNSON & JOHNSON	04-Sep-18	6,561	6,455
Tecfidera	Multiple Sclerosis	Biogen	29-Oct-19	3,638	4,017
Eylea	AMD	Regeneron	22-May-20	2,676	3,244
Soliris	Paroxysmal Nocturnal Hemoglobinuria	Alexion	16-Mar-21	2,590	2,921
Opdivo	Non-small cell lung cancer	Bristol		942	2,849
botox	Frown Lines	Allergan		1,976	2,772
Stelara	Psoriasis	JOHNSON & JOHNSON	01-Aug-21	2,474	2,746
Viekira	Hepatitis C	AbbVie		1639	2,000
Ibrance	Breast Cancer	Pfizer		723	1,919
Imbruvica	Lymphocytic Leukaemia	AbbVie		754	1806
Orkambi	Cystic Fibrosis	Vertex		351	1291

## 2.3.2. Year 2017



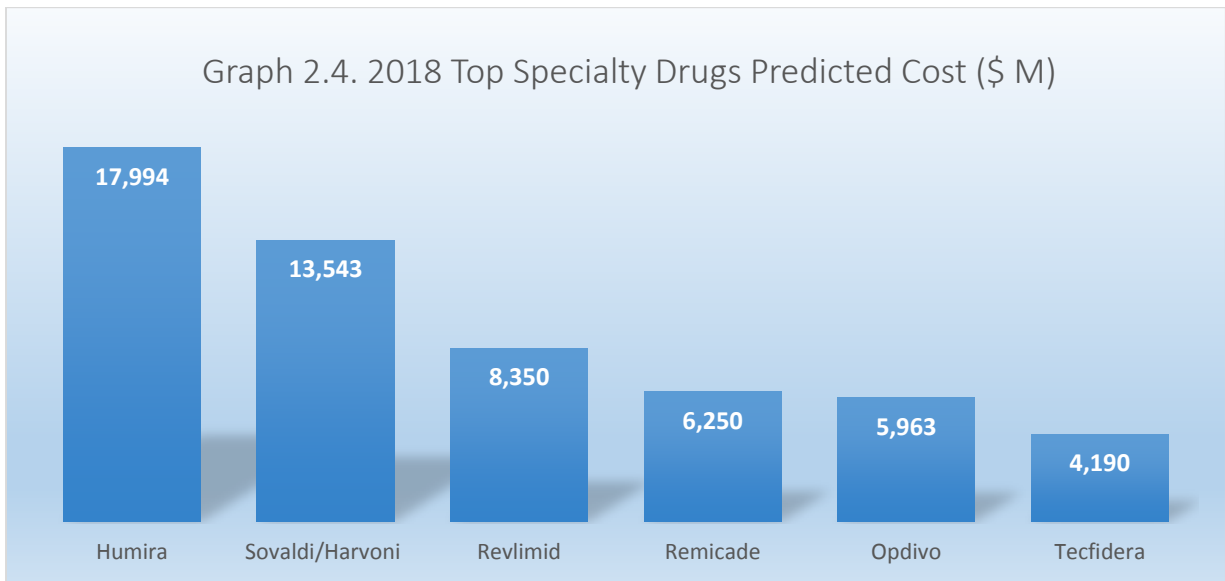
Source: Data are analyzed from (DrugAnalyst, 2016) (Patrick, 2016) (Nisen, 2016)

**Table 2.3. 2017 Top Specialty Drugs (\$ M)**

Drug	Indication	Company	Patent Expiry	2017
Humira	Rheumatoid Arthritis	AbbVie	31-Dec-16	17,220
Sovaldi/Harvoni	Hepatitis C	Gilead		16,306
Revlimid	Multiple Myeloma	CELG	04-Oct-19	7,585
Remicade	Rheumatoid Arthritis	JOHNSON & JOHNSON	04-Sep-18	6,375
Tecfidera	Multiple Sclerosis	Biogen	29-Oct-19	4,900
Opdivo	Non-small cell lung cancer	Bristol		4,542



### 2.3.3. Year 2018

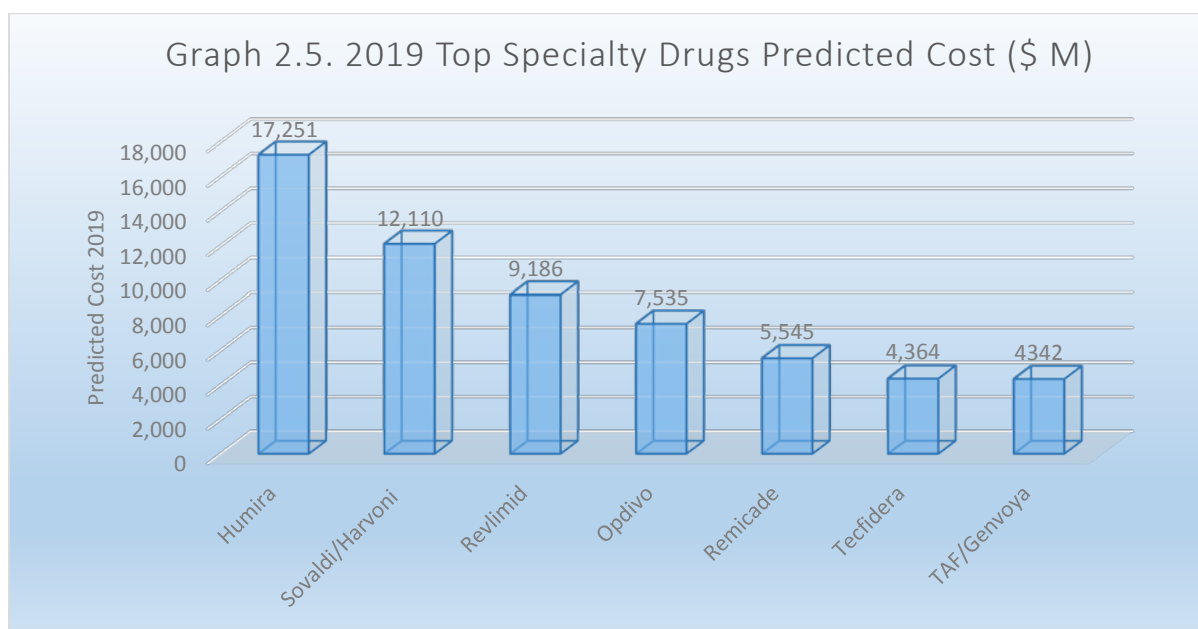


Source: Data are analyzed from (DrugAnalyst, 2016) (Patrick, 2016) (Nisen, 2016)

*Table 2.4. 2018 Top Specialty Drugs (\$ M)*

Drug	Indication	Company	Patent Expiry	2018
Humira	Rheumatoid Arthritis	AbbVie	31-Dec-16	17,994
Sovaldi/Harvoni	Hepatitis C	Gilead		13,543
Revlimid	Multiple Myeloma	CELG	04-Oct-19	8,350
Remicade	Rheumatoid Arthritis	JOHNSON & JOHNSON	04-Sep-18	6,250
Opdivo	Non-small cell lung cancer	Bristol		5,963
Tecfidera	Multiple Sclerosis	Biogen	29-Oct-19	4,190

## 2.3.4. Year 2019



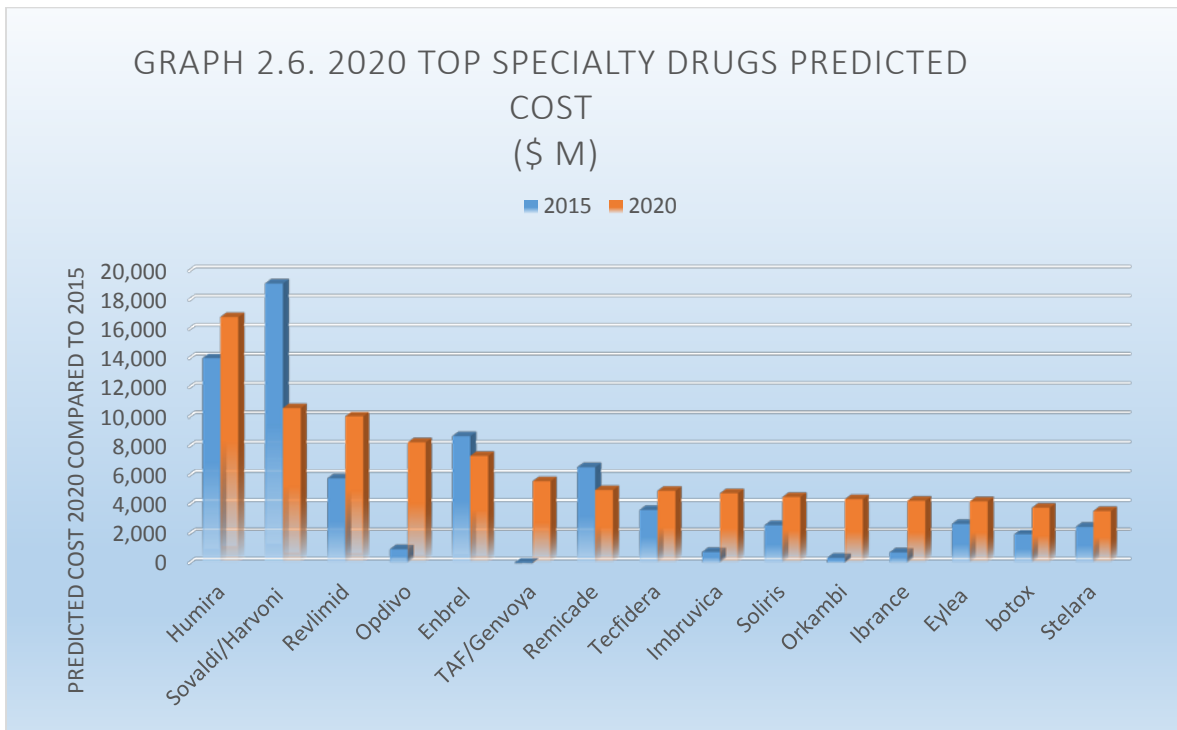
Source: Data are analyzed from (DrugAnalyst, 2016) (Patrick, 2016) (Nisen, 2016)

**Table 2.5. 2019 Top Specialty Drugs (\$ M)**

Drug	Indication	Company	Patent Expiry	2019
Humira	Rheumatoid Arthritis	AbbVie	31-Dec-16	17,251
Sovaldi/Harvoni	Hepatitis C	Gilead		12,110
Revlimid	Multiple Myeloma	CELG	04-Oct-19	9,186
Opdivo	Non small cell lung cancer	Bristol		7,535
Remicade	Rheumatoid Arthritis	JOHNSON & JOHNSON	04-Sep-18	5,545
Tecfidera	Multiple Sclerosis	Biogen	29-Oct-19	4,364
TAF/Genvoya	HIV	Gilead		4342

### 2.3.5. Year 2020

By 2020, we predicted Humira as the biggest drug with compound annual growth rate(CAGR) 3.7% from 2015 to 2020, because the lack of biosimilar drugs and the large population of patients with rheumatoid arthritis. Followed it, Socaldi and Harvoni will still be the second biggest drug by 2020, even it will decrease with a -11.7% CAGR.



Source: Data are analyzed from (DrugAnalyst, 2016) (Patrick, 2016) (Nisen, 2016)

**Table 2.6 2020 Top Specialty Drugs (\$ M)**

<b>Drug</b>	<b>Indication</b>	<b>Company</b>	<b>Patent Expiry</b>	<b>2015</b>	<b>2020</b>	<b>CAGR</b>
Humira	Rheumatoid Arthritis	AbbVie	31-Dec-16	14,014	16,838	3.70%
Sovaldi/ Harvoni	Hepatitis C	Gilead		19,140	10,582	-11.20%
Revlimid	Multiple Myeloma	CELG	04-Oct-19	5,801	10,021	11.60%
Opdivo	Non-small cell lung cancer	BMS		942	8,273	54.40%
Enbrel	Rheumatoid Arthritis	Amgen, Pfizer	01-Apr-29	8,697	7,343	-3.30%
TAF/Genvo ya	HIV	GIL		45	5608	162.50%
Remicade	Rheumatoid Arthritis	J&J*	04-Sep-18	6,561	5,000	-5.30%
Tecfidera	Multiple Sclerosis	Biogen	29-Oct-19	3,638	4,949	6.30%
Imbruvica	Lymphocytic Leukemia	ABBV		754	4779	44.70%
Soliris	Paroxysmal Nocturnal Hemoglobinuria	Alexion	16-Mar-21	2,590	4,524	11.80%
Orkambi	Cystic Fibrosis	Vertex		351	4376	65.60%
Ibrance	Breast Cancer	PFE		723	4,267	42.60%
Eylea	AMD	REGN	22-May-20	2,676	4,229	9.60%
botox	Frown Lines	Allergan		1,976	3,791	13.90%
Stelara	Psoriasis	J&J*	01-Aug-21	2,474	3,559	7.50%

\* J&J is company JOHNSON & JOHNSON

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## ***2.4. Analysis of Specialty Drugs Disruptor***

We categorized potential disruptors in specialty drugs in two clusters. The first disruptor is the potential increasing in the cost of specialty drugs that have been approved in the last two years. The second disruptor is the increment in the total cost due to new drugs approvals in the next five years. In this section, we quantify the specialty drugs cost separately.

For the first cluster, we found six specialty drugs which were approved in the last two years. They can represent the specialty drugs in recent two years, because of their huge cost. Moreover, we have following observations which indicate that the cost due to this class of drugs will increase rapidly. Take Opdivo, which was approved in 2014, as an example, the predicted cost of it will increase from 942 million dollars in 2015 to 8273 million dollars in 2020, which implies a 54.43% average annually growth rate in the following five years. This significant increasing trend is common in this cluster. Besides, we summed up the cost in this cluster, and the total cost of these drugs will be 115.15 billion dollars within the next five years. It indicates that the average annually cost will be approximately 23.03 billion dollars in the future five years (Table 2.7). Since the annual growth rate for each drug is high and the total cost is very substantial, we conclude that the class of approved specialty drugs in last two years is a disruptor.

According to the cost projection of potential drugs that will be approved in the next five years from DrugAnalyst Consensus Database, we ranked them by their costs and selected top ten drugs as our future approved drugs. By adding up the costs of the top ten specialty drugs, we got the total potential cost in the next five years, which will be 15.5 billion dollars (Table 2.8). Due to such a substantial cost, we argue that the class of potential drugs that will be approved in the future is unquestionable to be a disruptor for the healthcare industry.

**Table 2.7 New Approved Specialty Drugs 2016 - 2020 (\$ M)**

Market Date	Drug	Indication	Company	Total Cost
2014	Opdivo	Non-small cell lung cancer	BMS	\$29,162
2015	TAF/Genvoya	HIV	Gilead	\$13,854
2015	Imbruvica	Lymphocytic Leukaemia	AbbVie, Johnson & Johnson	\$28,535
2014	Imbruvica	Lymphocytic Leukaemia	Johnson & Johnson	\$12,072
2015	Orkambi	Cystic Fibrosis	Vertex	\$14,450
2015	Ibrance	Breast Cancer	PFE	\$17,072
Total				\$115,145

Source: Data are analyzed from (DrugAnalyst, 2016)

**Table 2.8 Specialty Drugs in Pipeline Predicted Cost 2016 -2020 (\$M)**

Drugs	Company	Inhibitor	Phase	Total Cost
Ozanimod	CELG	Multiple Sclerosis	III	\$1,096
Elagolix	AbbVie	Endometriosis	III	\$1,450
AUSTEDO	TEVA	Chorea / Dyskinesia and Huntington's Disease	Field	\$1,463
ARN-509	JOHNSON & JOHNSON	Prostate Cancer	III	\$1,483
ANACETRA PIB	Merck	Dyslipidaemia	III	\$1,269
VELIPARIB	AbbVie	Breast Cancer	III	\$1,470
Abemaciclib	Lilly	Breast Cancer	III	\$2,203

Source: Data are analyzed from (DrugAnalyst, 2016)

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## ***3. Pandemic***

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### 3.1. Purpose and Background

A pandemic is an epidemic of infectious disease that has spread through human populations across a large region. In general, the outbreak of pandemics always starts with the variation of a novel animal virus, which makes it possible to infect human and spread directly among people. The uncertainty of the virus variation makes it difficult to detect the possibility of the pandemic outbreak until a visible population is infected. Besides, the cost per patient of the pandemic is also higher than other diseases due to lack of previous cases. Both of the huge number of infectious cases and the high per person cost result in a substantial amount of inpatient claim to the insurance company.

Therefore, we suggest that the outbreak of a pandemic should be a disruptor for health care company in both the number of claims and claim severity. In this part, we will focus on the pandemic with high infectious and fatality rate.

In previous researches, deterministic model is widely used in pandemic and epidemic analysis. The most general method is SIR model, which contains three compartment: S = number susceptible, I = number infectious, and R = number recovered. All of the three compartments are varying over time. Hence, the pattern of the pandemic outbreak can be expressed in a system of differential equations:

$$\begin{aligned}\frac{dS}{dt} &= -\beta \frac{IS}{N} \\ \frac{dI}{dt} &= \beta \frac{IS}{N} - \gamma I \\ \frac{dR}{dt} &= \gamma I\end{aligned}$$

Assumed that:  $S(0) + I(0) = N, R(0) = 0$

This model is very simple but efficient in low fatality rate pandemic but it does not fit our requirement in this case. Hence, we constructed another model based on the similar idea.



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## 3.2. Model, Method and Analysis

In order to predict potential cost for different pandemics, we constructed a stochastic model to simulate the spread pattern and cost of pandemic under different scenarios and calculated the expectation and standard deviation of the potential cost.

### 3.2.1. Model

We used four compartments S, I, R and D to depict the pattern of the pandemic, in which the first three are as same as the SIR model and D = number dead due to the pandemic. Instead of the deterministic model, we added stochastic part into the model. The transfer period for each step is 1 day.

Firstly, we assumed the mortality rate  $q_d$ , the infectious rate  $\beta$ , and the recovery rate  $q_r$  are functions of the duration of infection for each case. Intuitively, the mortality rate would increase as the time of infection grows up and decrease in the later period of the infectious period. Besides, the recovery rate would maintain 0 at the early stage of the disease and increase as the time pass by. The infectious rate would be higher in the early stage and decline in the later stages.

Secondly, we constructed the transfer equation for each infectious patient at time t as follow:

$$N\_I(t) \sim \text{Binomial}(S, \frac{\beta(\tau_t)}{N})$$
$$I_{R,D,I}(t) \sim \text{three point distribution}(q_r(\tau_t), q_d(\tau_t), 1 - q_d(\tau_t) - q_r(\tau_t))$$

in which  $\tau_t$  is the number of infectious duration for the patient until time t. N\_I is the number of new infectious case caused by this patient.  $I_{R,D,I}$  is the transfer indicator of this patient, which indicates the state of next period.

Thirdly, we assumed that the transfer probabilities are the same for each person, and transfer process of infectious patients are independent with each other. Hence, the transfer equation of total number at time t can be expressed as follow:

$$\begin{aligned}
 S_t &= S_{t-1} - \sum_{j=1}^{I_{t-1}} N_{-} I(t-1; j) \\
 I_t &= I_{t-1} + \sum_{j=1}^{I_{t-1}} N_{-} I(t-1; j) - \sum_{j=1}^{I_{t-1}} I(I_{R,D,I}(t-1; j) = 'I') \\
 D_t &= D_{t-1} + \sum_{j=1}^{I_{t-1}} I(I_{R,D,I}(t-1; j) = 'D') \\
 R_t &= D_{t-1} + \sum_{j=1}^{I_{t-1}} I(I_{R,D,I}(t-1; j) = 'R')
 \end{aligned}$$

Based on this transfer equation we can calculate the cost of the pandemic as follow:

$$\text{cost} = \sum_{I_t=0}^N \sum_{j=1}^N I(I_{R,D,I}(t; j) = "I") * C_{t,j}$$

### 3.2.2. Assumption

Based on the characteristics of the general high infectious rate and mortality pandemic, we have following assumptions:

- a) The initial number of susceptible is controllable as we assume the pandemic can be detected in time and all the infectious cases are isolated in a small population after that. In this case, we assume  $S(0) = 1000$ ;
- b) The initial number of infectious case is 1.
- c) The death time follows a Poisson distribution in the multi-decrement analysis and there exists a maximum of in-patient days. There is also a minimum date for the infectious to recover, after that the recovery follows a Uniform distribution in the multi-decrement analysis.

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d) The infectious rate remains constant in the first half of the infectious period and falls down to a proportion of this constant later.

e) We assume all the people in the infectious state will recover at the end of the simulation period since the length of the period is large enough. According to the historical pandemic data, we assume this period to be 200.

f) The daily cost per each patient follows uniform distribution between the maximum and the minimum of the daily cost.

Hence, in this model we have 6 parameters:

a) Mean survival time for the death case:  $\lambda$

b) The maximum stay in-patient time:  $\max\_stay$

c) The minimum stay in-patient time for recovery cases:  $\min\_stay$

d) The initial infectious rate:  $\beta$

e) The cut-down proportion of infectious rate in the late stage:  $r$

f) Minimum daily cost and maximum daily cost:  $(c_m, c_M)$

### 3.2.3 Scenario

In order to predict the potential cost, we created three scenarios based on the data of outbreak of Ebola virus in West Africa 2014 (Morrow):

a) Severe scenario (based on the data of outbreak of Ebola 2014):

$$\lambda = 21, \beta = 0.16, \max\_stay = 100, \min\_stay = 14, r = 0.5$$

$$c_m = 8000, C_M = 24000$$

b) Moderate scenario (80% of the Severe scenario)

$$\lambda = 16.8, \beta = 0.128, \max\_stay = 100, \min\_stay = 11.2, r = 0.4$$

$$c_m = 6400, C_M = 19200$$

c) Slight scenario (50% Of the Severe Scenario)

$$\lambda = 10.5, \beta = 0.08, \max\_stay = 100, \min\_stay = 7, r = 0.25$$

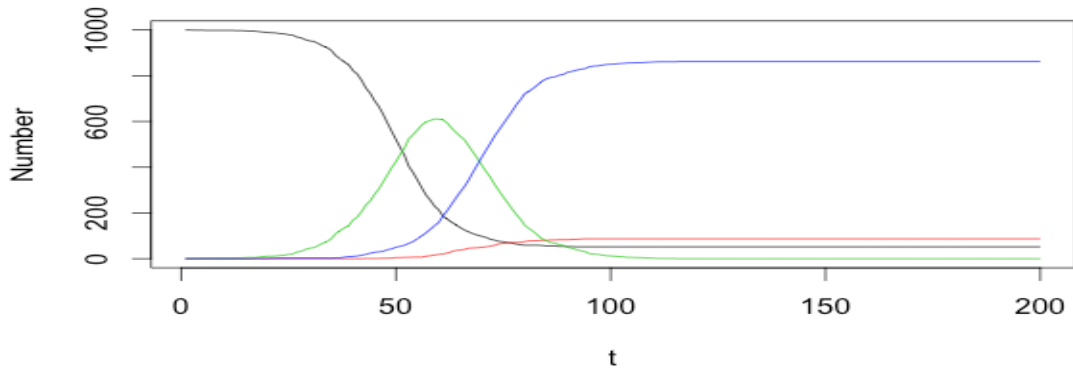
$$c_m = 4000, C_M = 12000$$

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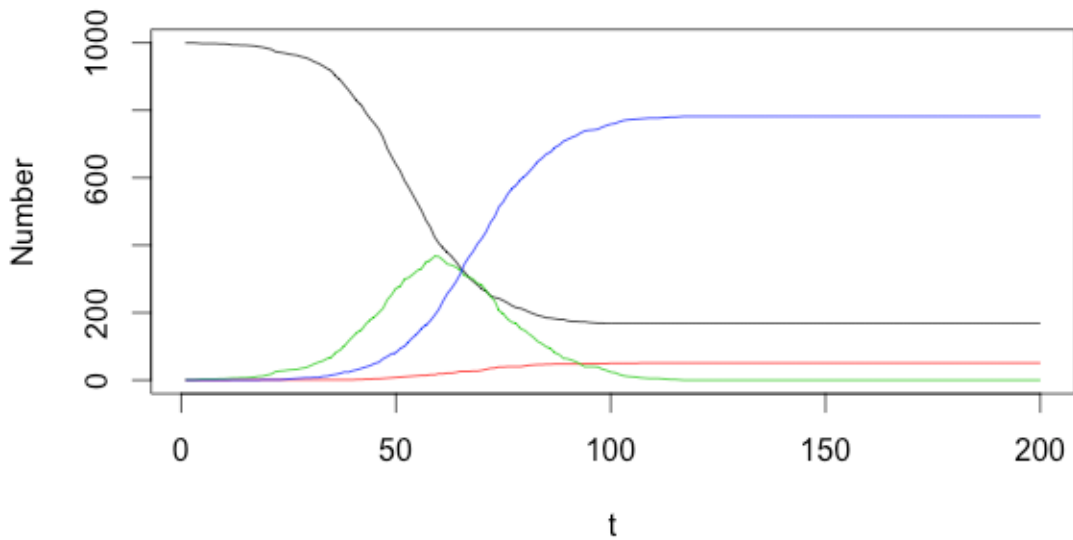
### 3.2.3. Duration, Inpatient day and Spread probability

Under the three scenarios above, we simulated the spread pattern of the pandemic

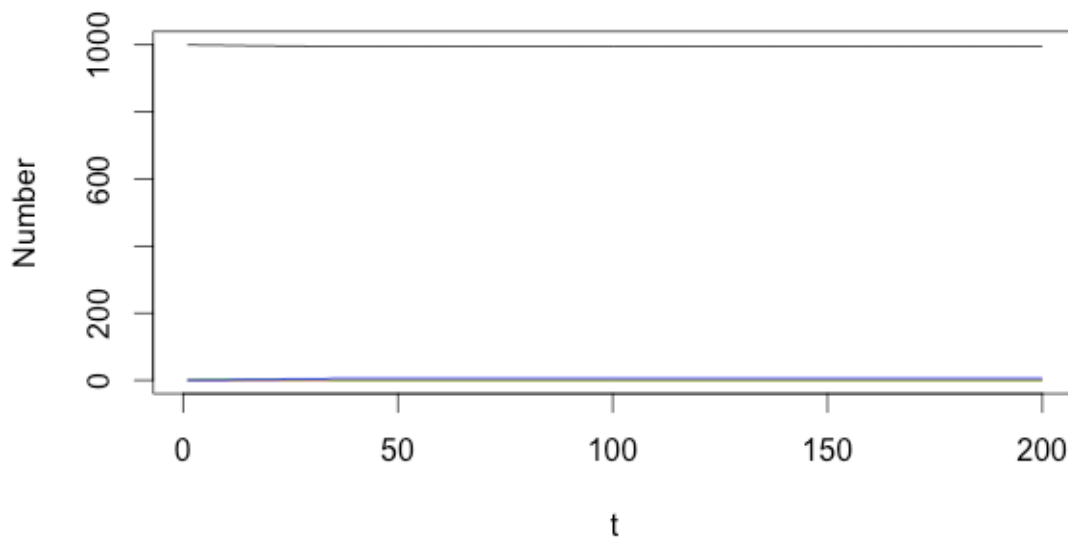
**Graph 3.1. Spread pattern for Severe Scenario**



**Graph 3.2. Spread pattern for Moderate Scenario**



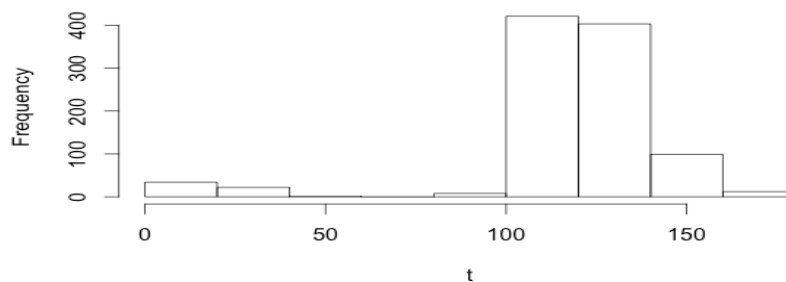
**Graph 3.3. Spread pattern for Slight Scenario**



From the simulation, we can find that under the severe scenario, the pandemic will spread swiftly as the infectious number increases sharply and end as the recovery rate grows and the death of the infectious cases. Under the Moderate scenario, the peak of the Infectious number is lower than the severe case, which will casus less treatment cost compared with the former scenario. The pandemic will not widespread under the Slight scenario as the infectious ratio is really small compared with the mortality rate.

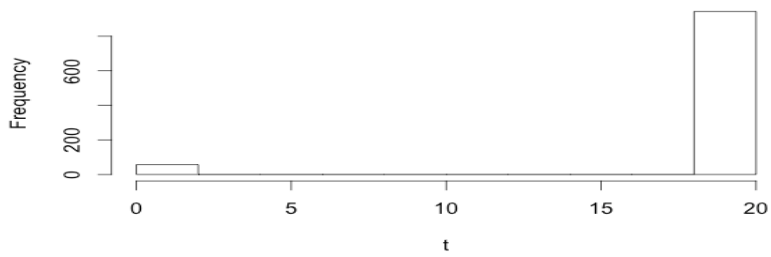
Simulating the process 1000 times, we can get the expected spread span and average number of inpatient day per patient under each scenario.

**Graph 3.4. Histogram of Spread Period(Severe Scenario)**



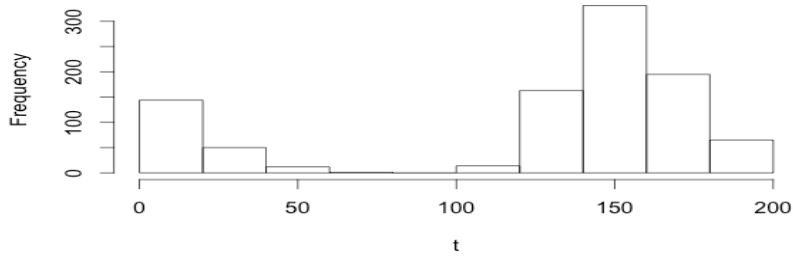
**Graph 3.5.**

**Histogram of Average Inpatient Day(Severe Scenario)**



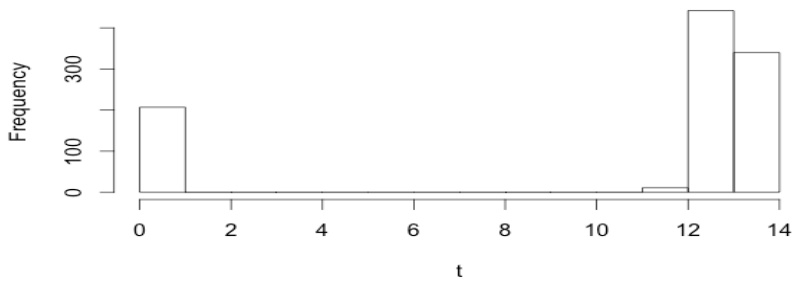
**Graph 3.6.**

**Histogram of Spread Period(Moderate Scenario)**



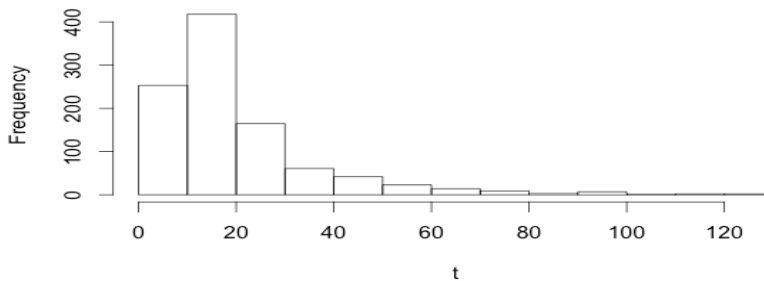
**Graph 3.7.**

**Histogram of Average Inpatient Day(Moderate Scenario)**

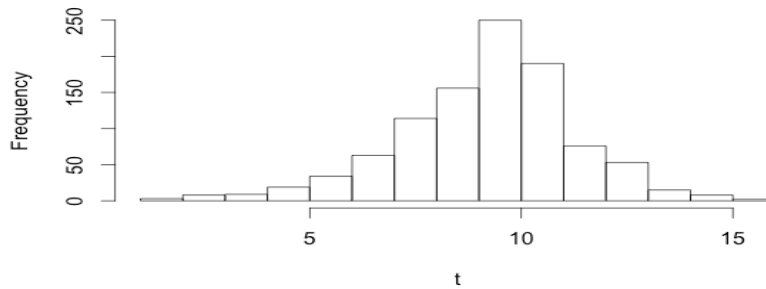


**Graph 3.8.**

**Histogram of Spread Period(Slight Scenario)**



**Graph 3.9. Histogram of Average Inpatient Day(Slight Scenario)**



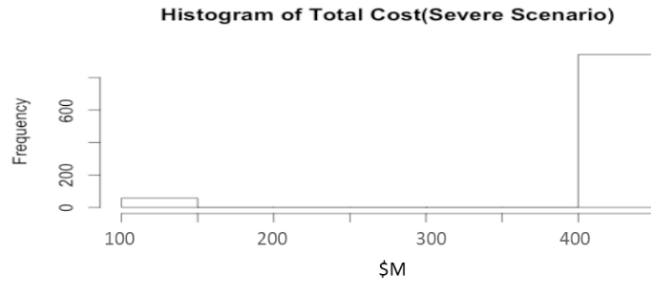
**Table 3.1. Results of Duration, in patient days and Probability of widely spread**

	<b>Average in patient days</b>	<b>Duration</b>	<b>Probability of widely spread</b>	<b>Std. of Average Inpatient Day</b>	<b>Std. of Duration</b>
Severe	19.84	117.22	95.40%	1.09	26.85
Moderate	15.63	125.66	82.30%	1.49	59.72
Slight	9.48	20.22	29.60%	2.07	16.2

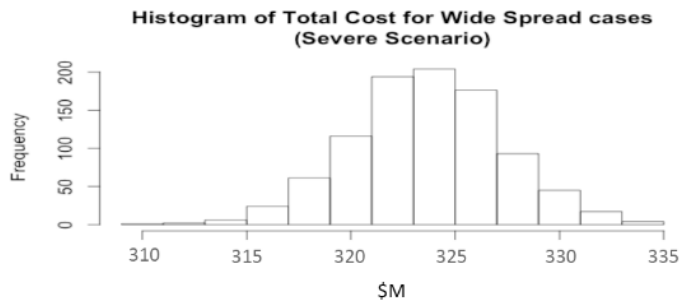
From the result, we have following observations. Firstly, the pandemic as the severe scenario will result in a longer duration and inpatient days, which intends to lead to a higher claim number. Secondly, under the moderate scenario, the pandemic will cause shorter inpatient period but a longer duration, Finally, under the Slight scenario, the probability that the pandemic will not widely spread is really high, which indicates that it will not cause problems for the company in this cases.

### 3.2.4. Predicted Cost

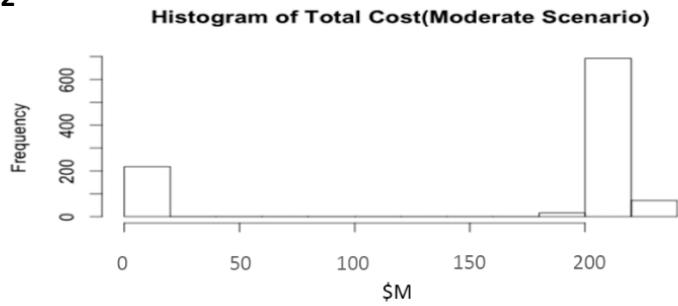
Graph 3.10



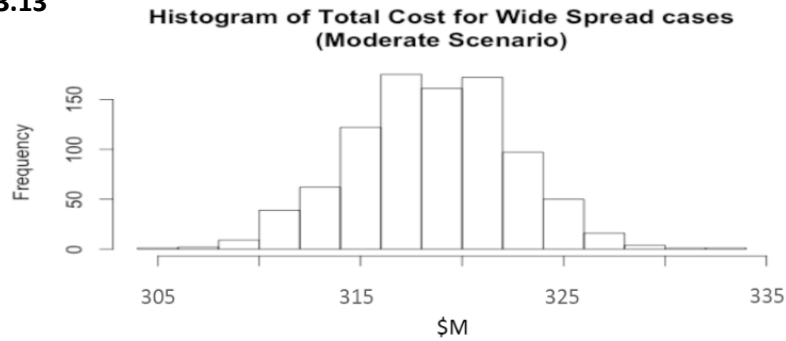
Graph 3.11



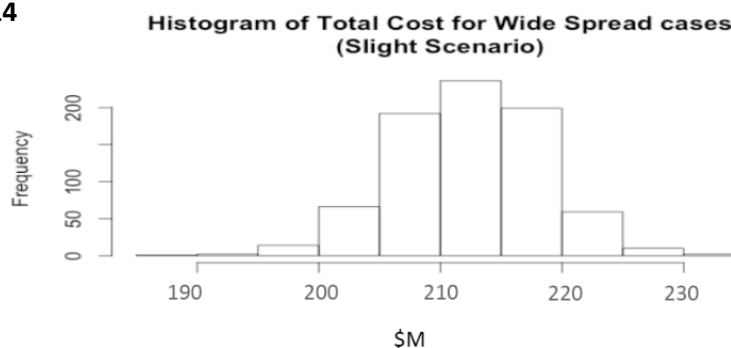
Graph 3.12



Graph 3.13





**Graph 3.14****Table 3.2 Results of total cost**

	Mean(million)	Std.	VaR(99%)	CVaR(99%)
Severe	300.49	73.9	327.1	328.01
Moderate	165.98	87.9	225.96	227.69
Slight	0.7193	1.37	5.91	1.02

### 3.3. Conclusion

From the results of our simulation, we draw following conclusions. Firstly, a pandemic with high infection rate and fatality will have a large probability to widespread even under an effective control assumption. This implies that the simulated cost can be regarded as a lower bound for the cost of a real pandemic. Secondly, the amount of the total cost is determined by the infection rate, and the average pandemic inpatient days are much larger with higher infection rate. Finally, the duration of this kind of pandemic is very short. Also, a substantial claim amount in such a short period will be a significant challenge to the company’s liquidity.

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## 4. Strategies to CEO

According to our analysis and projection above, we provide strategies for insurance company to handle these three disruptors.

For chronic diseases, we can help educate the insured to prevent chronic diseases and reduce health risk factors. Because chronic diseases are lasting long and have bad influences on our life quality, it's important for people to form healthy habits. Also, insurance companies can come up with different long-term policies for individuals with a different number of chronic conditions.

To manage and prepare for the potential disruptors in the drug segment, insurance company should evaluate the potential increment annually and prepare sufficient fund for it. Besides, encouraging the utilization of generic drugs or relatively lower cost drugs is a very effective strategy. In addition, to keep watching the specialty drugs in the pipeline is a reliable approach to forecasting and prepare for the potential disruptors in the future.

To prepare for the potential outbreak of pandemics, we have three suggestions. Firstly, insurance company could set a higher deductible to the pandemic claims in order to reduce the claim severity. Secondly, insurance company could also use reinsurance to transfer the risk of pandemic outbreak. Thirdly, a sufficient amount of fund should be prepared in order to handle the emergent pandemic claims.

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