POPUP Project

Research Report

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Chapter 1

Introduction

The most precarious populations have a higher rate of premature mortality than the rest of the population, and are associated with more cardiovascular, respiratory, osteoarticular and psychiatric pathologies [16] [15] [18] [14]. These patients are more hampered by certain barriers to access to care such as structural or financial barriers and have a high rate of refusal of care [6] [3] [4] [13] [8] [5]. However, in France, patients who declare that they have given up care for financial reasons are more likely to use emergency services, which act as an interface between the city and the hospital and are available and accessible to all at all times [7]. In addition, low-income patients are associated with more frequent use of emergency departments and more often present complications for certain acute pathologies such as strokes, coronary pathologies or asthma attacks [17] [12] [2] [11].

Among precarious populations, migrant populations and even more so those who are illegally present in France are particularly vulnerable. They report poor health more frequently and face more barriers to access to care (illegibility of procedures and systems, communication difficulties, health literacy). Even though there are certain measures such as the "State Medical Support" (AME, "Aide Médicale d'Etat"), which allows health insurance to cover health care (prevention, consultations, hospitalization), the complexity of the administrative procedures and the existence of waiting periods before benefiting from them have an impact on migrants' health care pathways, leading them to forego certain care or to turn to emergency services as a last resort [9].

A specific system called "Urgent and Vital Care" (SUV, "Soins Urgents et Vitaux") allows patients who are not eligible for any other aid or insurance to be treated for any urgent and vital pathology and to benefit from costs that are fully covered by the health insurance [1]. The beneficiaries of this benefit are most often patients of foreign origin who are asylum seekers waiting for the AMO (Base system, "Assurance Maladie Obligatoire") or foreigners in an irregular situation who are not eligible for the AME (waiting period). Expenditure under this scheme thus amounted to €100 million in 2018 [10].

While migrant and precarious patients most often enter the French health care system through an emergency room consultation because they do not have access to general medicine and to the system of common rights, there are few studies describing and comparing the care pathways and, in particular, the hospital stays of patients covered by the SUV system with those covered by the AME, CMU-C (Supplementary Universal Health Coverage,"Couverture maladie universelle Complémentaire") and AMO.

The present work, code-named POPUP, aims at performing such comparisons both qualitatively and quantitatively and analyzing these differences of patients and hospital stays in terms of pathology involved, level of severity, medical care provided, duration and cost.

Furthermore, the legislator has recently introduced changes in the framework for access to health care for migrant populations: introduction of a stamp for affiliation to the AME in 2011, abolished in 2013, and introduction in 2020 of a three-month waiting period for asylum seekers before they can benefit from the AMO. These changes in access to the AME may have had an impact on the use of the SUV system for sick migrant populations.

Consequently, this work has three complementary objectives. It aims at :

1. Describing a novel french hospital stays dataset, and characterizing the key top level differences between the 4 systems of interest.
2. Capturing a quantitative measure of precariousness by comparing social health care systems (SUV, AME, CMU-C) to the base system (AM0). These indicators will be associated with stays duration, critical care duration and overall stay cost.
3. Leveraging econometric models in order to answer the following questions:
   (a) Is system membership a key factor for explaining stay costs ?
   (b) What is the impact of the aforementioned 2013 and 2020 public policies on the patient contingent per system ?

Chapter 2

Descriptive analysis of hospital care access systems

This part focuses on describing from different standpoints a *PMSI* (*Programme de médicalisation des systèmes d'information*) sample. This dataset consists of about 3 million french hospital stays observations from 2011 to 2021 across the 4 hospital care access systems of interest (AME, SUV, CMU-C and AMO)

The exploratory analysis conducted aims at characterizing the key top level differences between these systems. We start drawing the bigger picture by describing the demographics and geographical distribution of patients. Then, we dive into a thematic analysis whereby we try to apprehend, both generally and across time, stays and patients in various important dimensions such as *ghm* structure, condition criticality or costs. Finally, we focus on two specific topics that polarize noteworthy patterns: *Séances* CMD and *DOM-TOM* regions.

2.1 The bigger picture

2.1.1 Patient distribution with respect to systems

Number of patients per system
(all years combined)

SUV	57 276
AME	343 392
AMO hors CMU-C	527 849

Figure 2.1: Number of patients per system (all years included)

As Fig 1.1 shows, our PMSI sample loosely relates to the actual distribution of patients in each systems. The majority of french people belongs to the wider systems such as AMO for the most part and CMU-C which targets populations in need of extra financial support. AME, targeting specifically migrants, asylum seekers, represents nonetheless an important portion of the dataset. SUV, designed for undocumented patients in dyer need of hospital care is less represented group without about 60k patients from 2011 to 2022.

2.1.2 Patient gender distribution with respect to systems

Répartition par sexe de l'effectif des patients

(selon le dispositif, toutes années confondues)

raison	Homme	Femme
AME	38,48%	61,55%
AMO hors CMU-C	44,08%	55,93%
CMU-C	44,95%	55,07%
SUV	48,01%	52,01%

Figure 2.2: Breakdown by sex and by system of the number of patients (all years included)

There is a clear over-representation of women in all systems when we look at the sample globally. This importance is variable, spreading from 52% of the SUV population to over 61% for AME. In addition, Fig 1.2 allows us to observe the similarity of the gender breakdown between AMO and CMU-C, which rest in the middle of the spectrum, making the migrant targeted systems lying on both ends of this gradient of women over-representation.

2.1.3 Patient age distribution with respect to systems

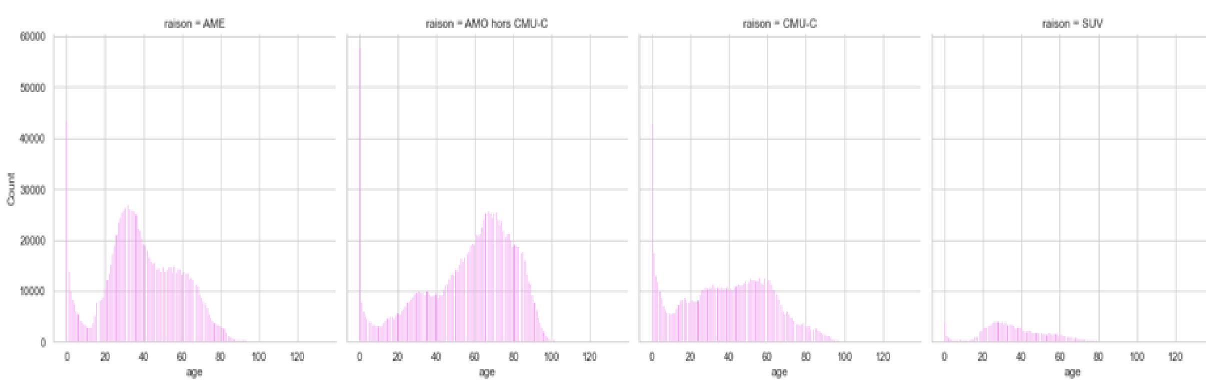


Figure 2.3: Breakdown by systems of the age distribution of patients (all years included)

From Fig 1.3 and 1.4, we can observe that SUV and AME are youngest systems, followed by CMU-C. AMO replicates the larger population and features senior patients as its main contingent. In more details, with a mean age of respectively 36 years and a median age of 34 years old SUV constitutes the youngest system with about 50% of its population lying between 25 and 47 year old. On the other end, AMO's mean and median age are, respectively, 55 and 61 year old with about 50% of its population ranging from 40 to 74 year old.

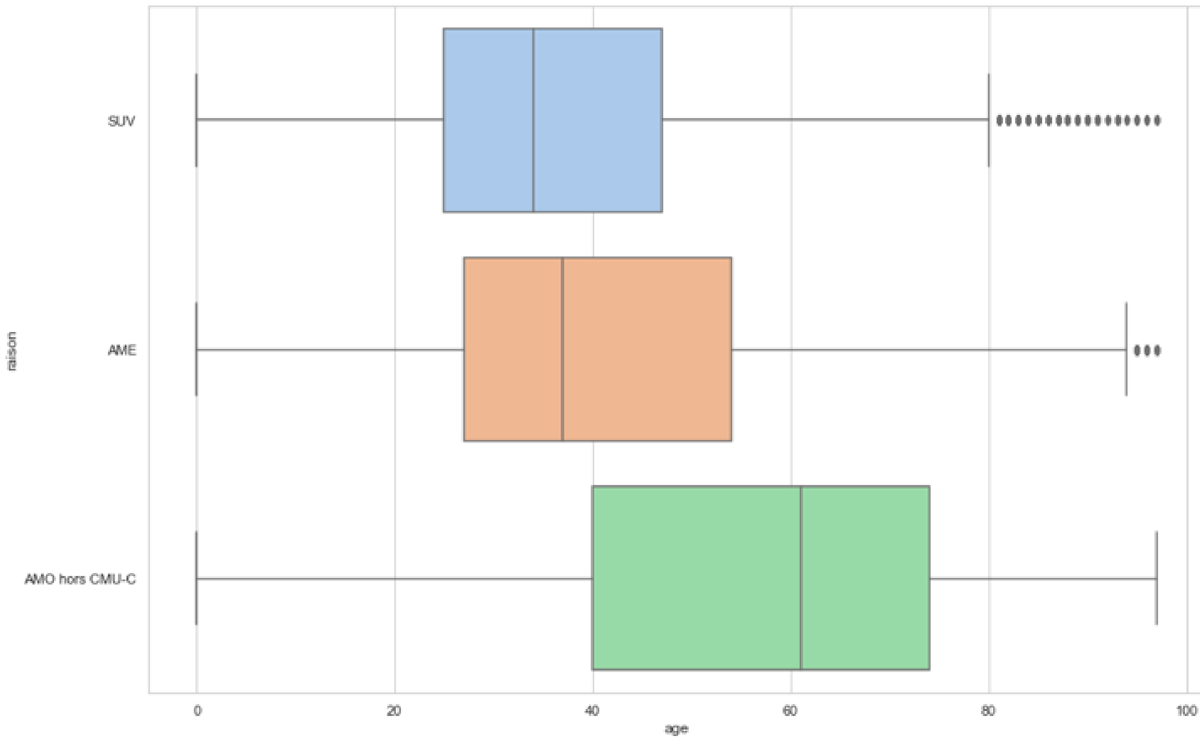


Figure 2.4: Boxplots by systems of the age distribution of patients (all years included)

2.1.4 Patient regional distribution with respect to systems

When we analyze patient regional distribution across systems we generally observe a polarization around the main metropolitan centers. The 4 following maps go beyond this approach by trying to apprehend the spatial distribution of a demographic index (patients per 1Ok inhabitants). The pattern that emerges is that SUV and AME patients are concentrated mainly in DOM TOM and the Paris metropolitan area. AMO and CMU-C are less polarized, spreading more evenly on the french territory. The high index number for Guyana for AMO is more revealing of a relatively low population than of significant patient number in this region relatively to others.

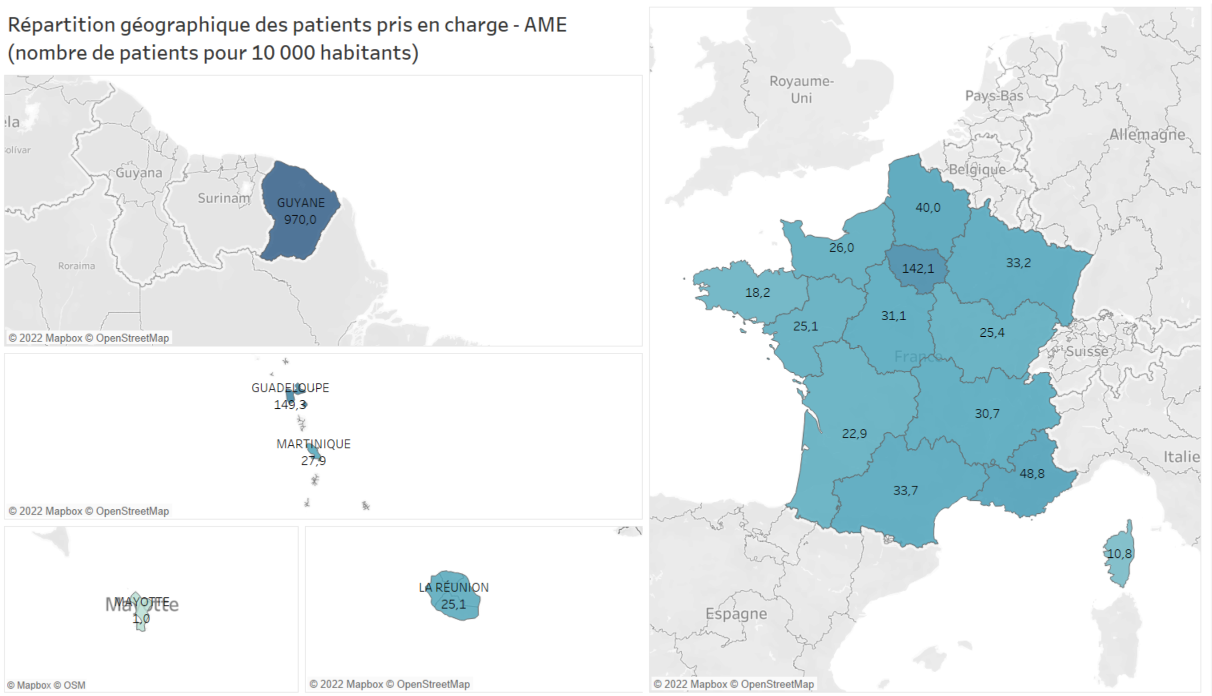


Figure 2.5: Regional distribution of AME patients (all years included)

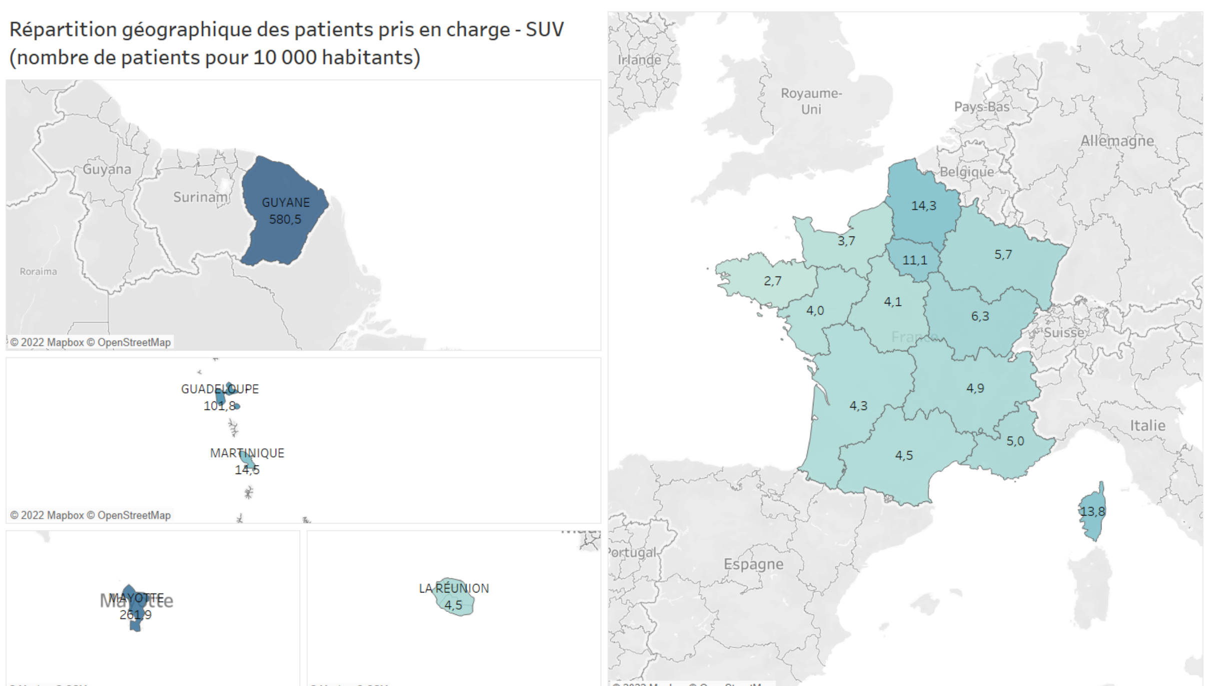


Figure 2.6: Regional distribution of SUV patients (all years included)

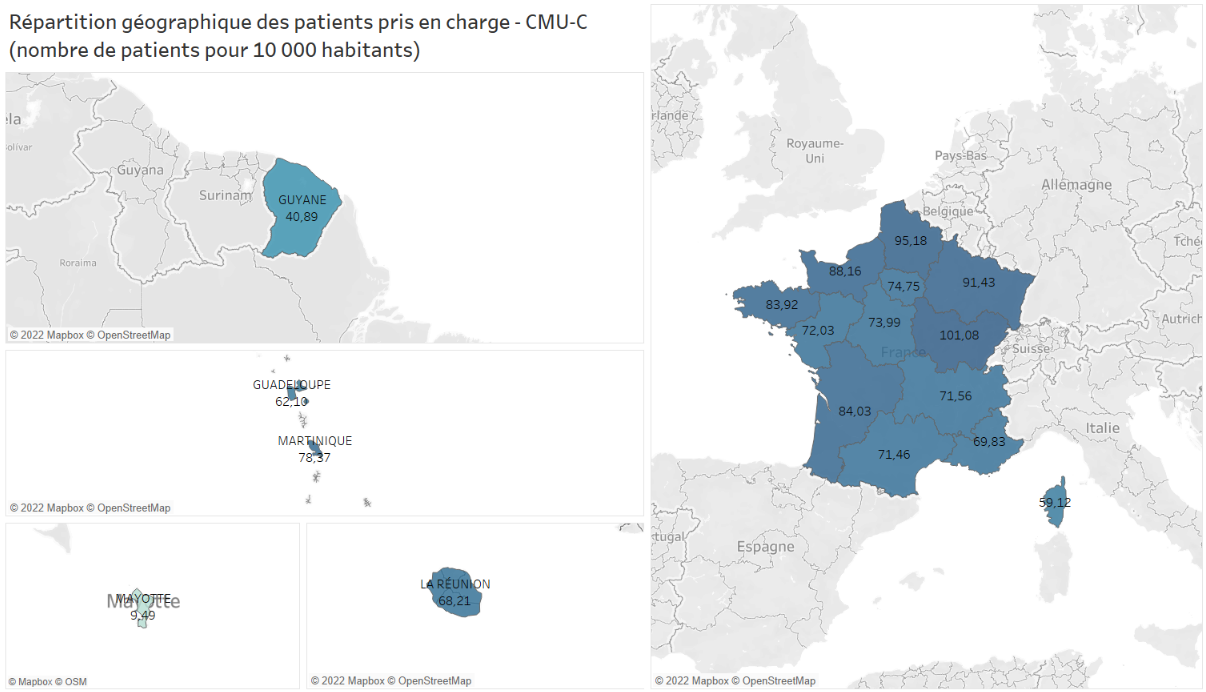


Figure 2.7: Regional distribution of CMU-C patients (all years included)

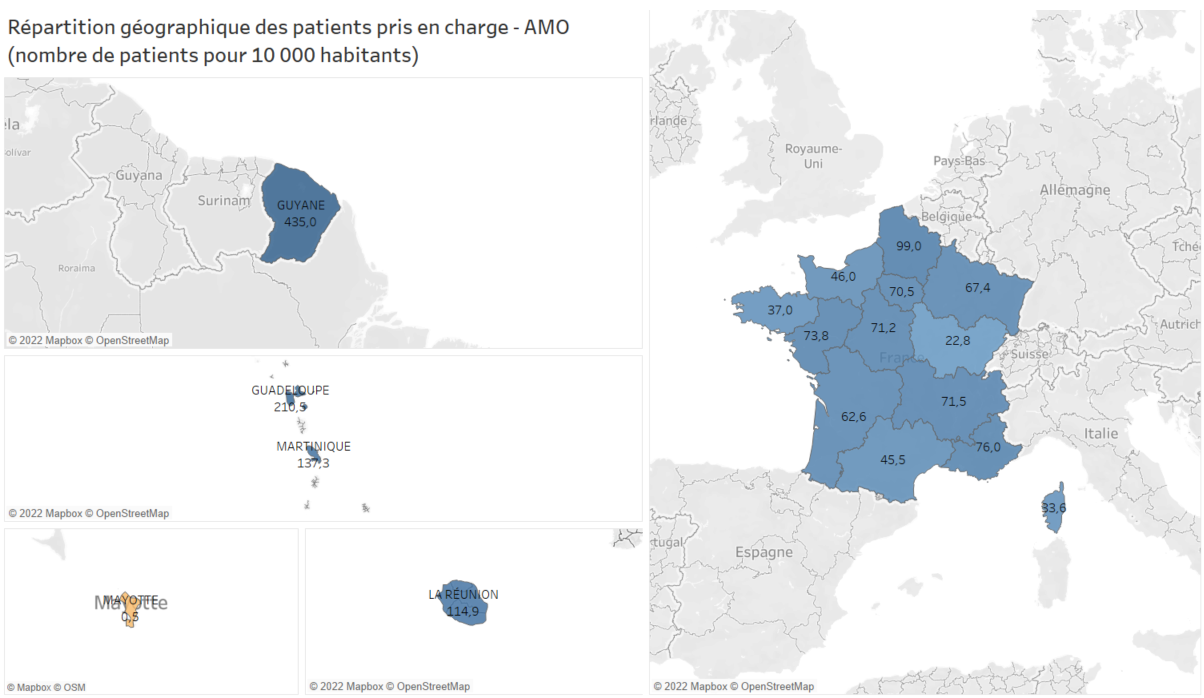


Figure 2.8: Regional distribution of AMO patients (all years included)

2.1.5 Evolution of stays regional distribution with respect to systems

When considering the dynamics of the regional stays distribution across systems, two general trends come up. The first one refers to a relative stability in the regional composition as it is the case for AMO base system troughout the 10 years of data available. We can also include AME in this category although it experienced a steady increase in the Guyane region share eating up the large portion that Ile-de-France originally had.

The second trend pattern is that of abrupt change in the composition as it can be observed for CMU-C and more so SUV. The sudden drop of Grand-Est region from about 15% in 2013 to approximately 5% of CMU-C's annual stays in 2014 testifies of an important regional reconfiguration that was maintained trough time as this share stayed in that range since then. Suv experience an even more blunt change in its regional structure as Mayotte region stays went from representing up to 15% of SUV annual stays to essentially zero since 2019.

evo_geo_AME_eng.png

Figure 2.9: Evolution of regional distribution of AME patients

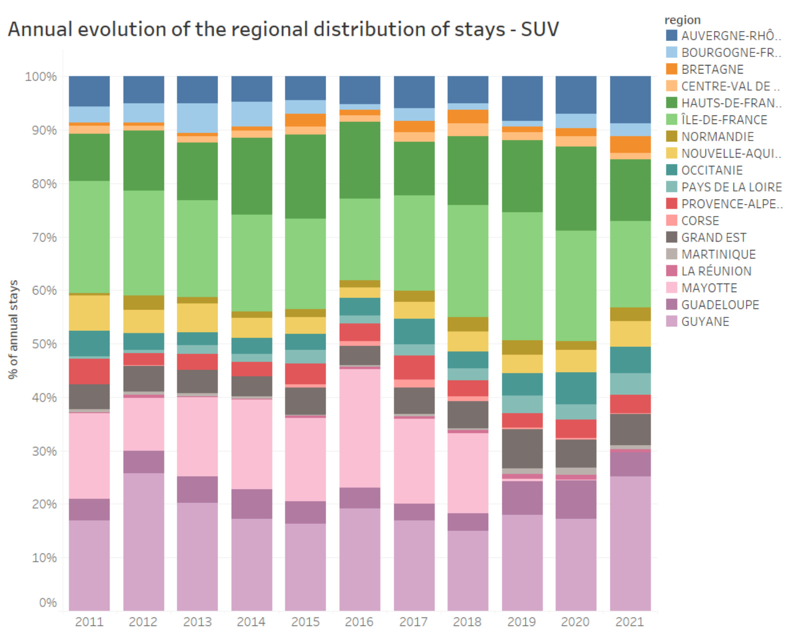


Figure 2.10: Evolution of regional distribution of SUV patients

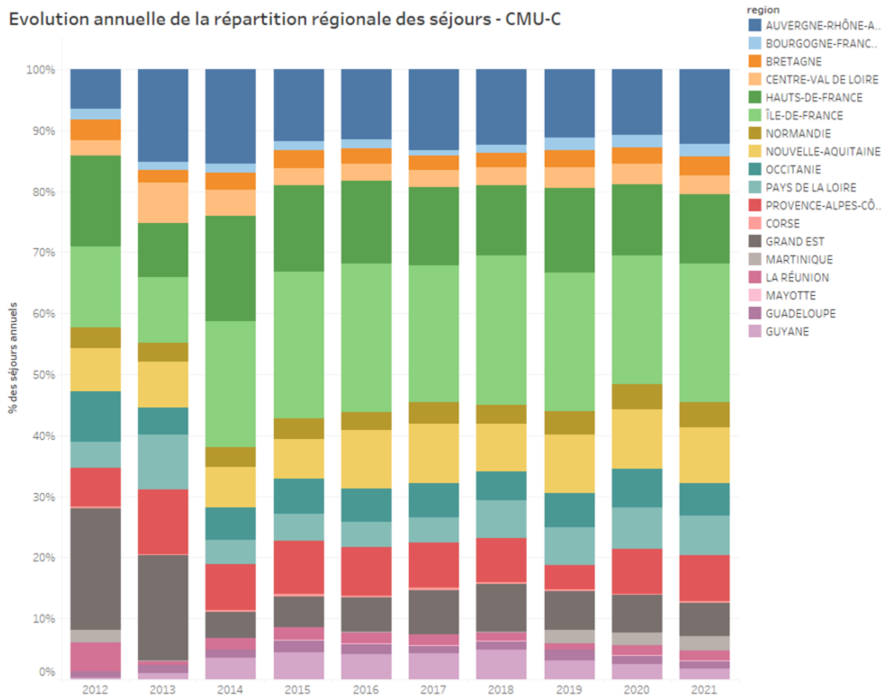


Figure 2.11: Evolution of regional distribution of CMU-C patients

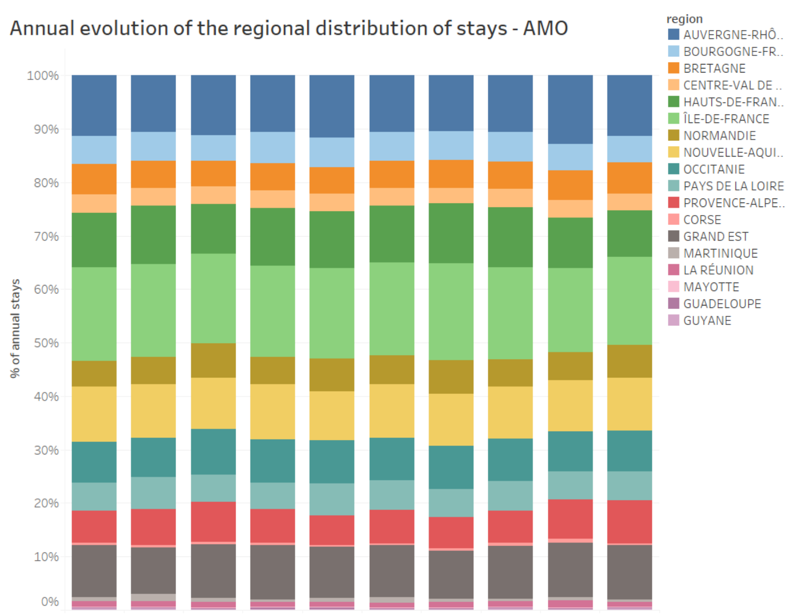
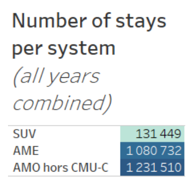


Figure 2.12: Evolution of regional distribution of AMO patients

2.1.6 Stays: total and mean number distribution with respect to systems

The total stays distribution follows the same ordering logic as the patients number distribution shown above. An interesting difference is the fact that AME's count is way near that of AMO's with a difference of about 200K stays.
This observation is confirmed by the high mean number of stays per patient displayed by AME at 3.1 stays, about 1 stay more than AMO and SUV and 1.5 stays more than CMU-C.


Number of stays per system
(all years combined)

SUV	131 449
AME	1 080 732
AMO hors CMU-C	1 231 510

Figure 2.13: Stays repartition across systems (all years included)

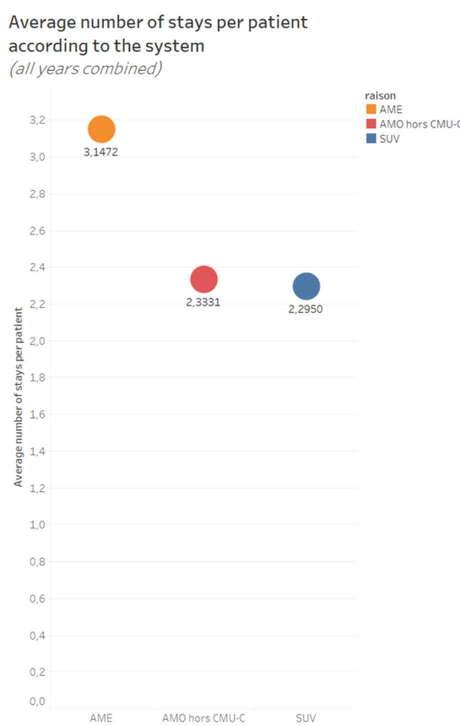


Figure 2.14: Mean stays number per patient repartition across systems (all years included)

2.1.7 Evolution of stays and patients counts

The dynamic profile of the yearly count of stays and patients is the same for every system. We can distinguish three groups. AME,AMO with a sizeable absolute increase from

2011/2012 to 2021 be it in terms of patients or stays. SUV with a steady absolute growth and these two dimension that double in the 10 years windows its initial 2011 counts. Finally, CMU-C exhibits a more erratic dynamic with an important drop between 2013 and 2014 followed by a steady increase the following years to retrieve its initial 2012 levels. Regarding mean stays count per patient, we observe an interesting convergence between SUV and CMU-C on one hand from respectively 1.5/1.6 stays to 1.8 stays over the period; and on the other hand AME and AMO from respectively 1.9/2.1 stays to 2.45 stays.

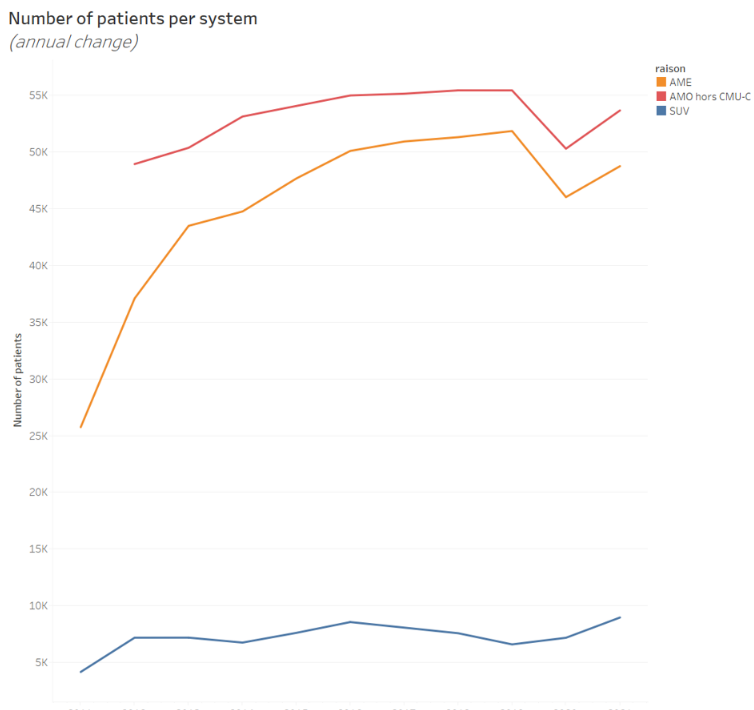


Figure 2.15: Yearly evolution of patient count across systems

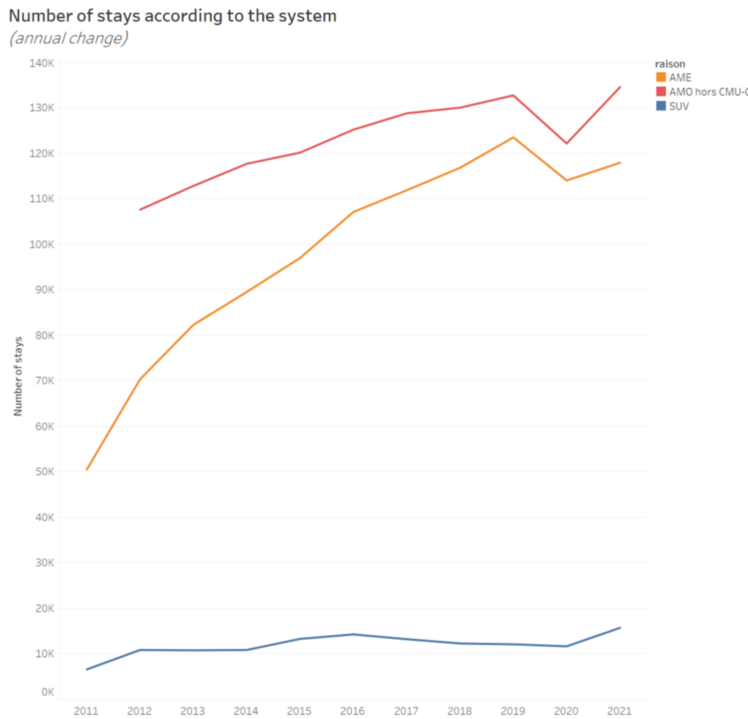


Figure 2.16: Yearly evolution of stays count across systems

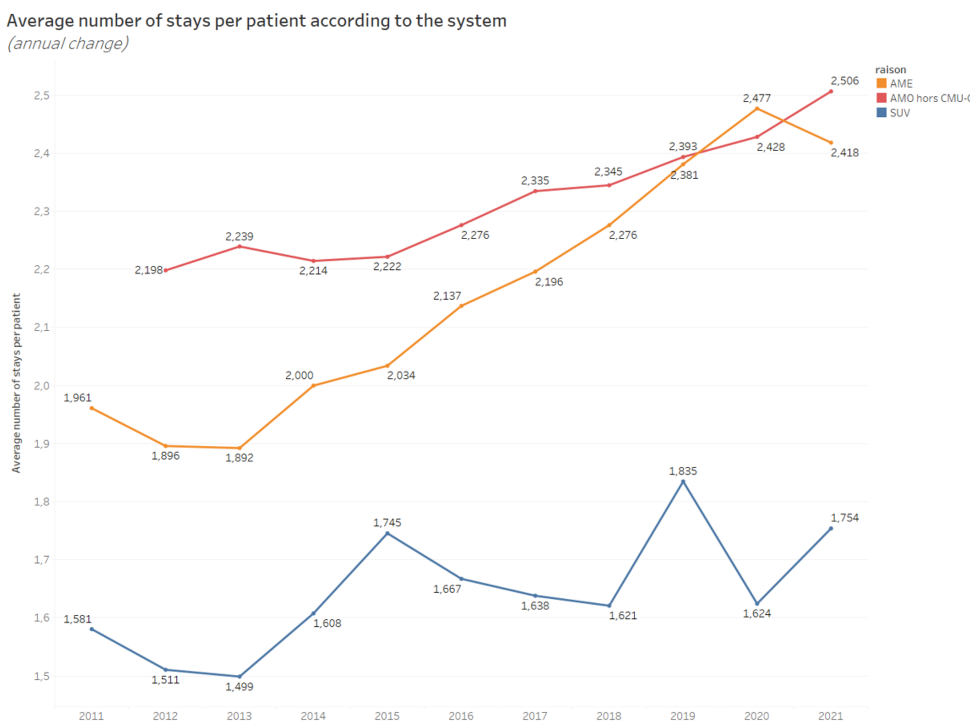


Figure 2.17: Yearly evolution of mean stays count per patient across systems

2.2 Thematic Analysis : *patients and stays level*

2.2.1 GHM structure per system

The analysis of the GHM structure of each system was done in several ways in an effort to highlight different dimensions underlying the stays.

This work was done according to two temporal dimensions :

1. *Statically* : taking into account the data from all years, we performed 4 types of study:
   (a) The first one consisted in shedding light upon the distribution of 2 big interventions blocks "Gynecology/Obstetrics", "Oncology".
   (b) The second approach is more granular and brought us to define 20 GHMs group that made sense given the GHMs and their isolated occurrences.
   (c) Finally, we looked at the distribution of GHMs associated with mortality.
   (d) *Dynamically* : exploring the yearly evolution of patients contingents for the most represented GHMs groups across all systems.

2.2.2 Big GHMs blocks distribution

We see a striking domination of obstetrics/gynecology themed GHMs for the migrant targeted systems SUV and AME. Oncology is the second contingent for this systems with a fraction of the dominant block patients. For the two more general systems, we observe more balanced patient contigents, with obstetrics/gynecolocy leading the way with "others" GHMs block. This suggests more fragmentation in GHMs for AMO and CMU-C.

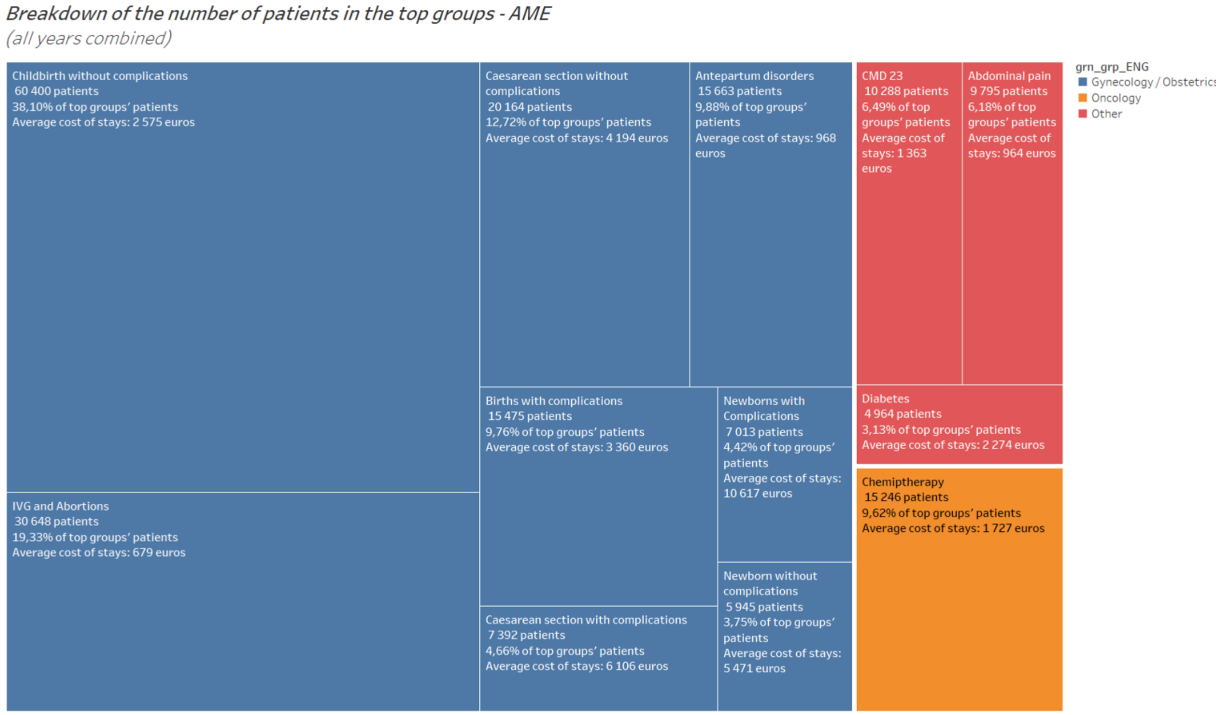


Figure 2.18: Big GHMs blocks distribution(patients, AME, all years included)

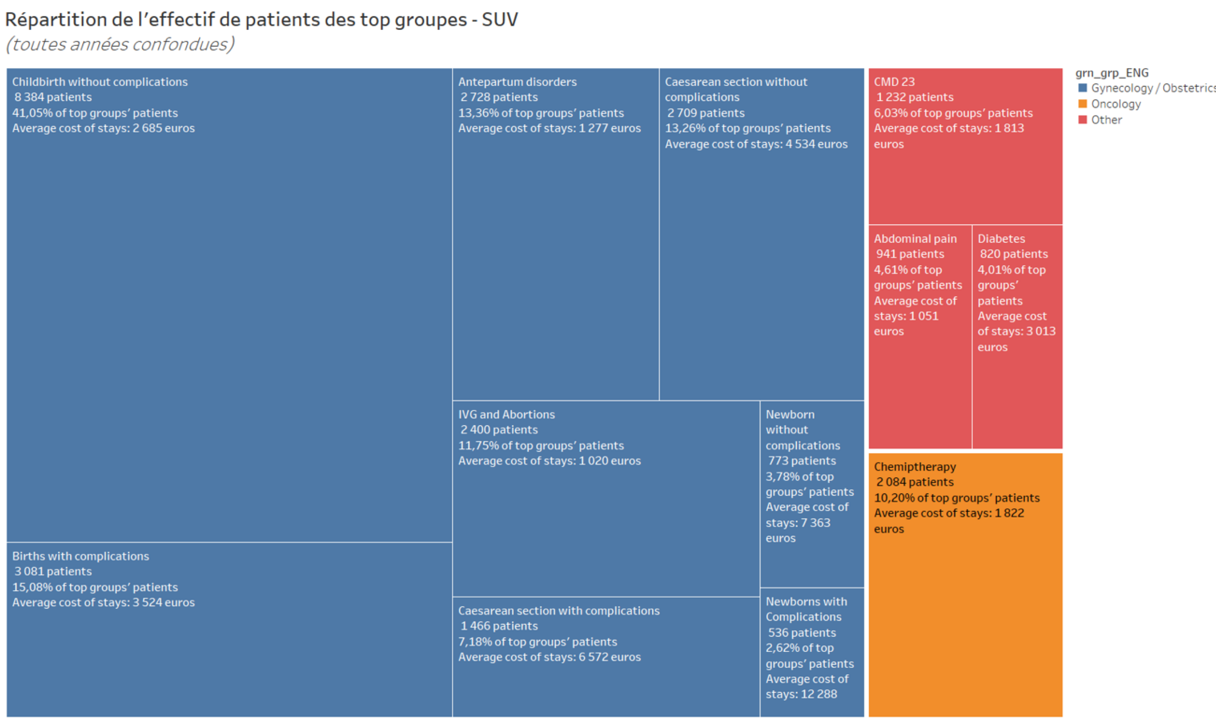


Figure 2.19: Big GHMs blocks distribution (patients, SUV, all years included)

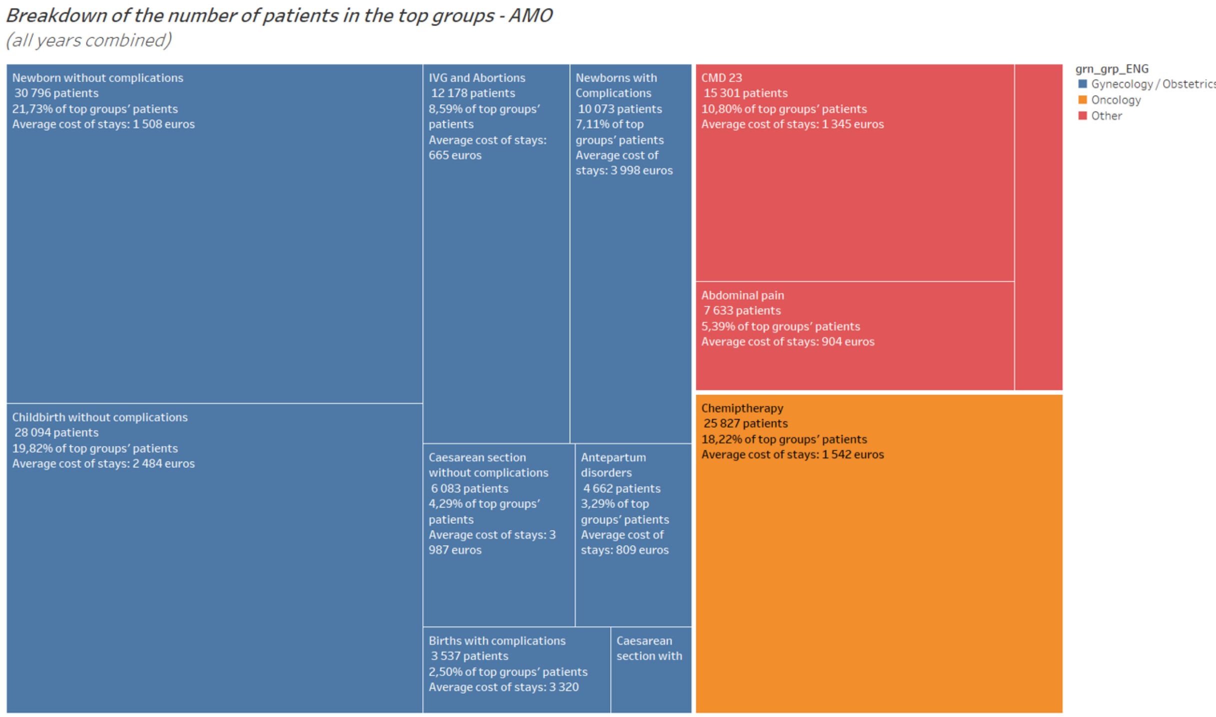


Figure 2.20: Big GHMs blocks distribution(patients, AMO, all years included)

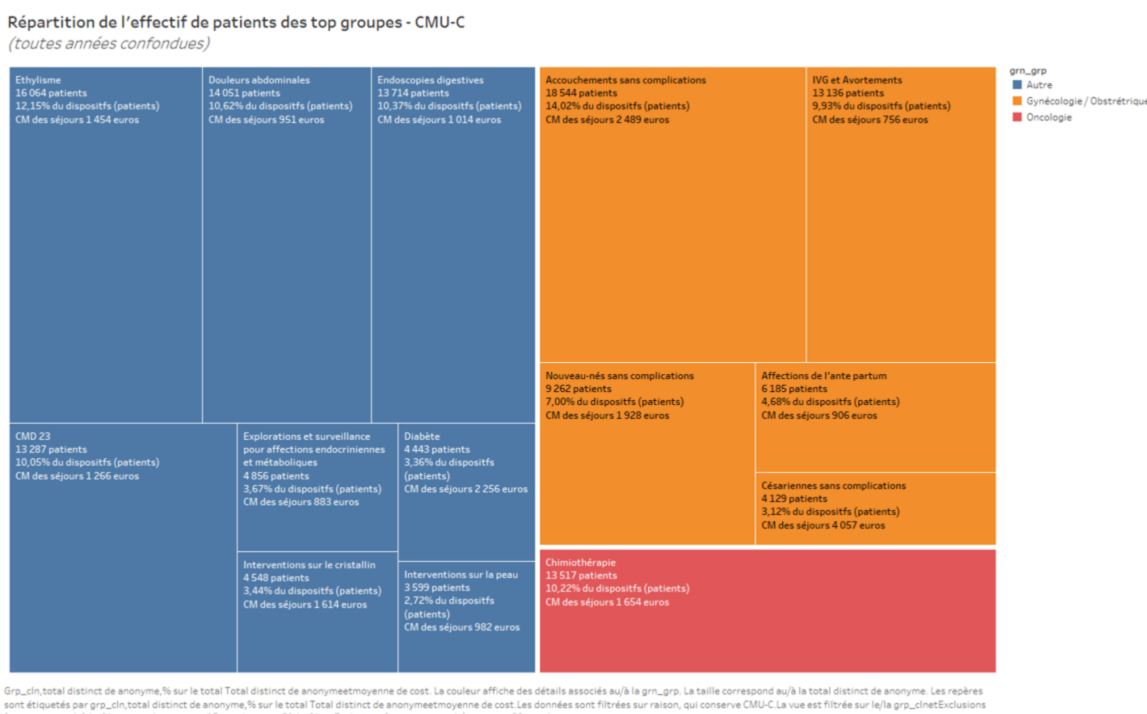


Figure 2.21: Big GHMs blocks distribution(patients, CMU-C, all years included)

2.2.3 Granular GHMs blocks distribution

The follwowing charts shed light upon a distinctive factor between SUV and AME. SUV's top 5 GHMs blocks all relate to gynecology and obstetrics, with about 10% of the system patients concerned with abortion "IVG". In addition, the second top GHM block evokes childbirth with complications, suggesting high precariousness within this system. In the other hand, AME still has 3 of its Top GHM blocks related to gynecology and obstetrics, however no mention of complications and presence of additional blocks related to chemotherapy and CMD23.

CMU-C's and AMO's granular GHM block distribution features way more fragmentation with top blocks related to obstetrics/genecology, chemotherapy, endoscopy, abdominal pain and alcoholism.

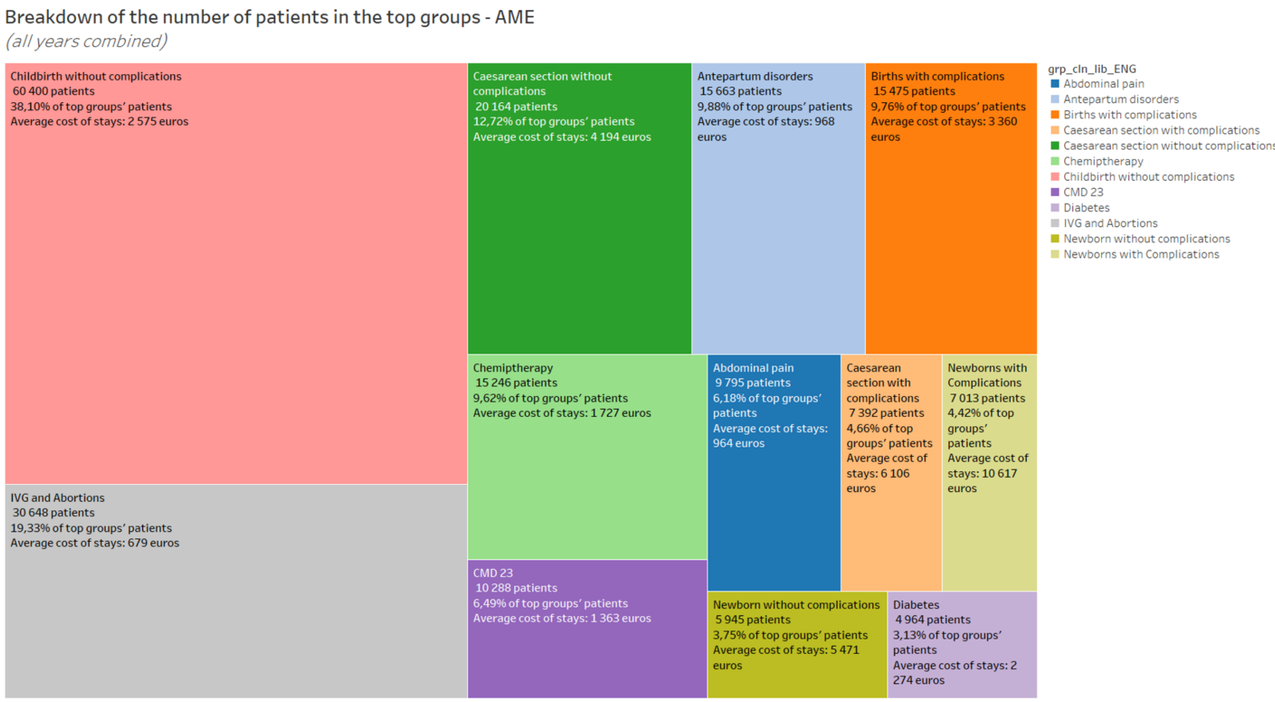


Figure 2.22: Granular GHMs blocks distribution(patients, AME, all years included)

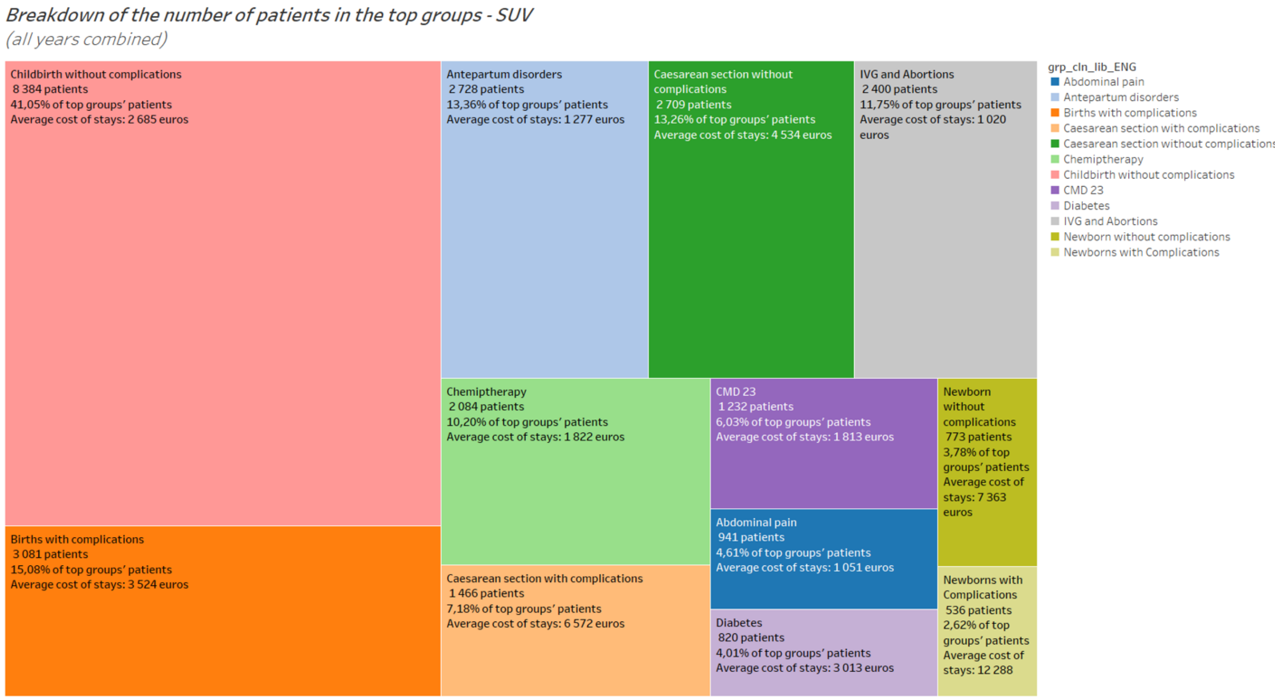


Figure 2.23: Granular GHMs blocks distribution (patients, SUV, all years included)

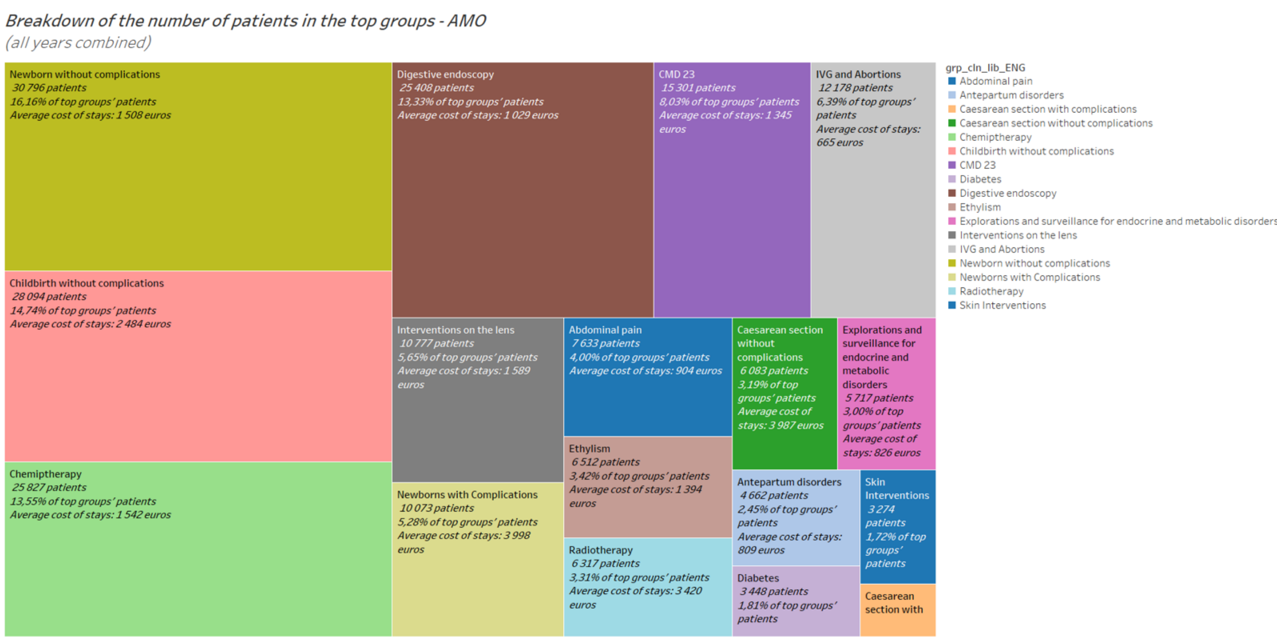


Figure 2.24: Granular GHMs blocks distribution(patients, AMO, all years included)

2.2.4 GHMs associated with mortality distribution

The data reveals that beyond the palliative care GHM that is dominant across all systems, there is some differentiating factors between systems. SUV features hepatobiliary

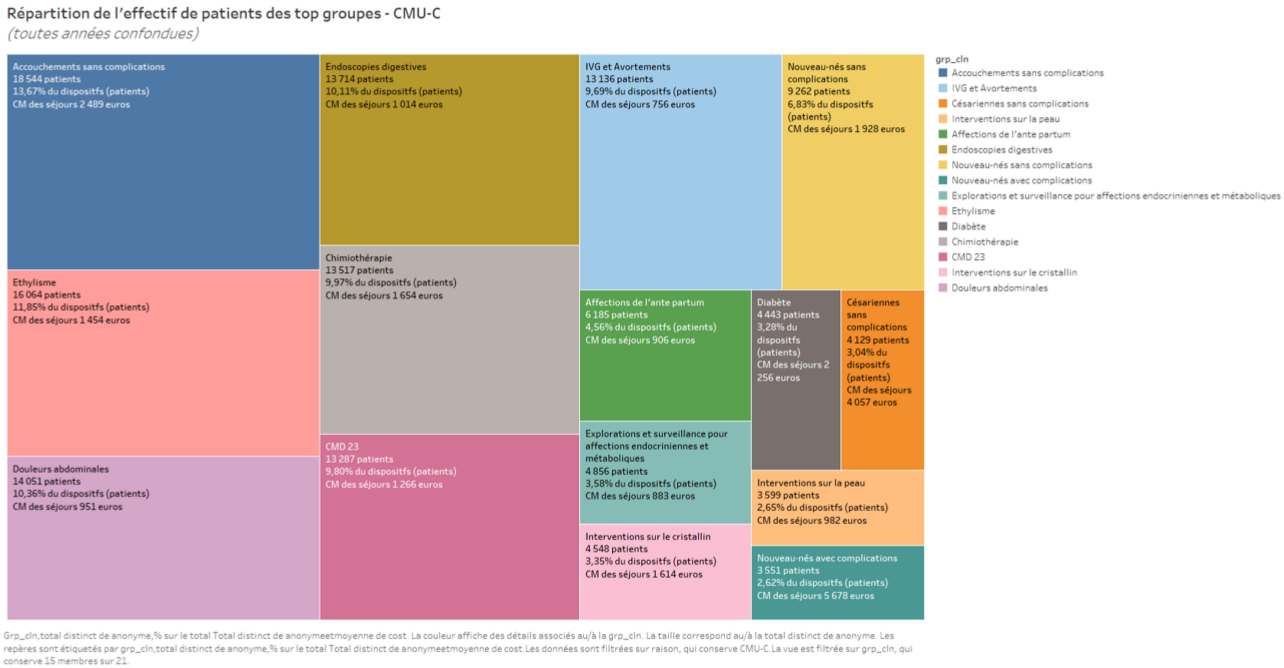


Figure 2.25: Granular GHMs blocks distribution(patients, CMU-C, all years included)

or pancreatic disorders, as well as respiratory infections and inflammations and premature newborn deaths as GHMs associated with death. Whereas AME's distribution is less diverse and contains specifically late newborn deaths and respiratory infections and inflammations GHMs. AMO and CMU-C death related GHMs distribution is again more fragmented and features GHMs pertaining to oncology, respiratory disorders and cardiology.

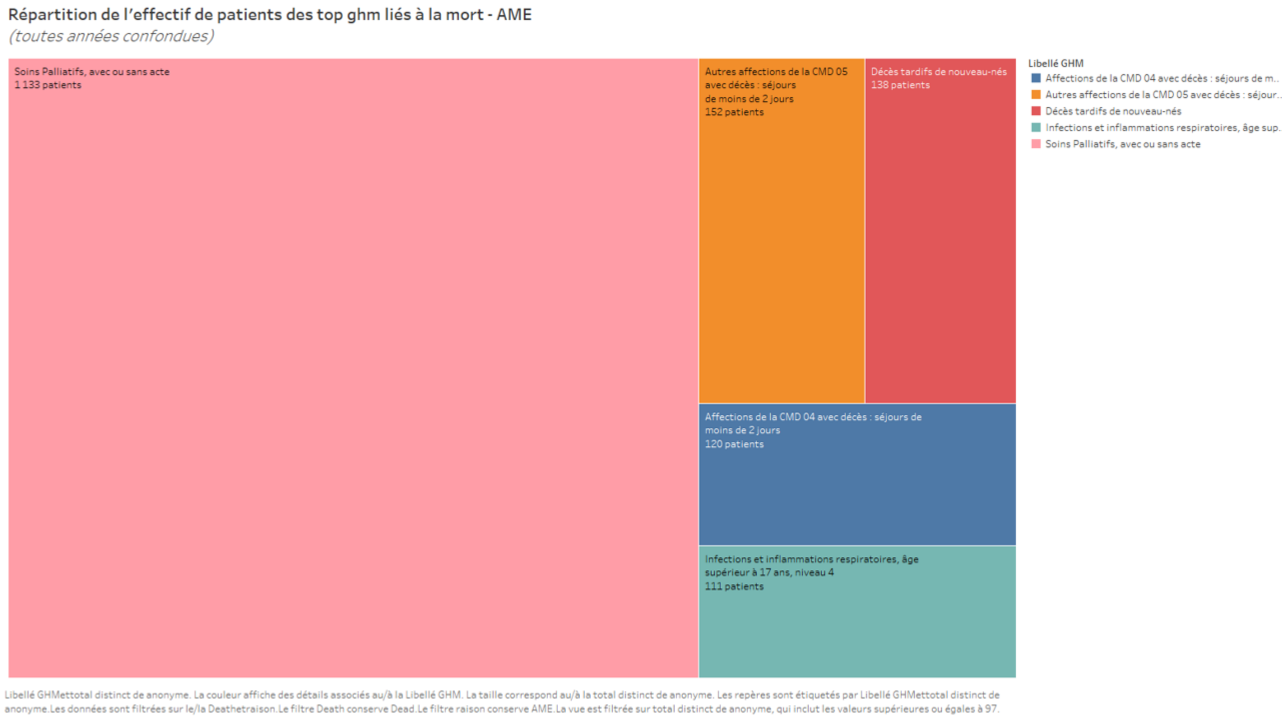


Figure 2.26: Death GHMs blocks distribution(patients, AME, all years included)

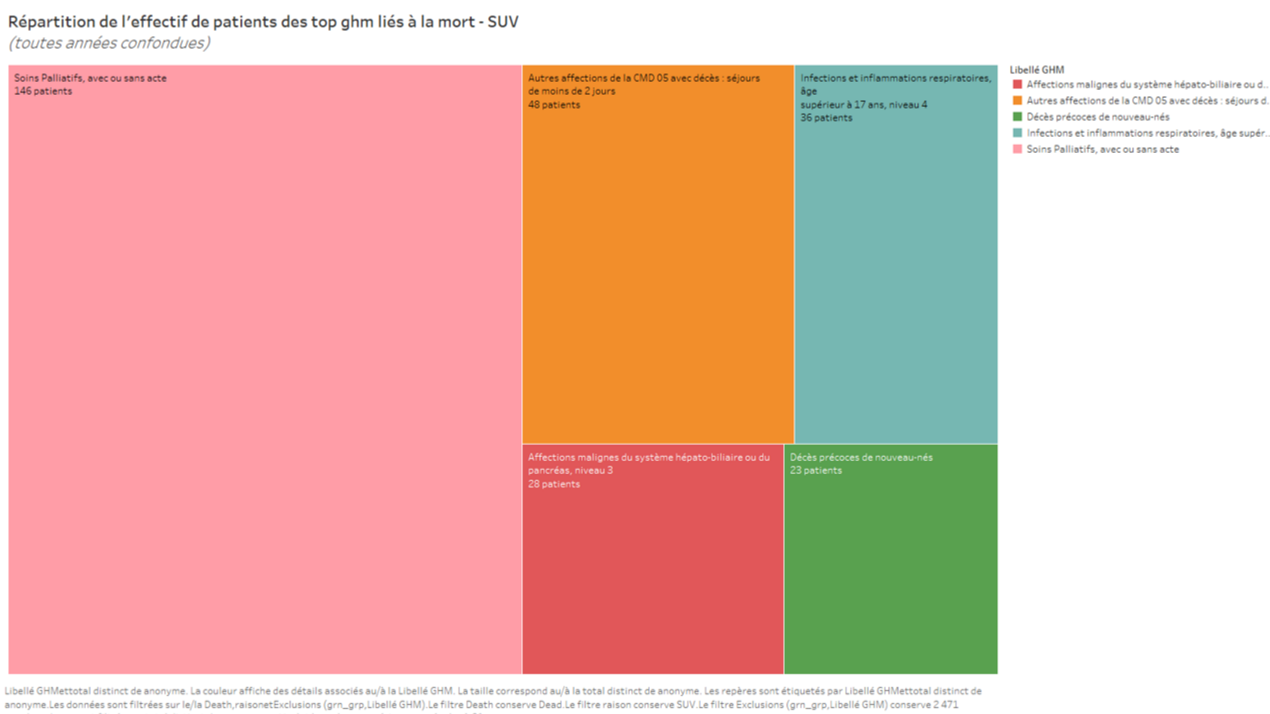


Figure 2.27: Death GHMs blocks distribution(patients, SUV, all years included)

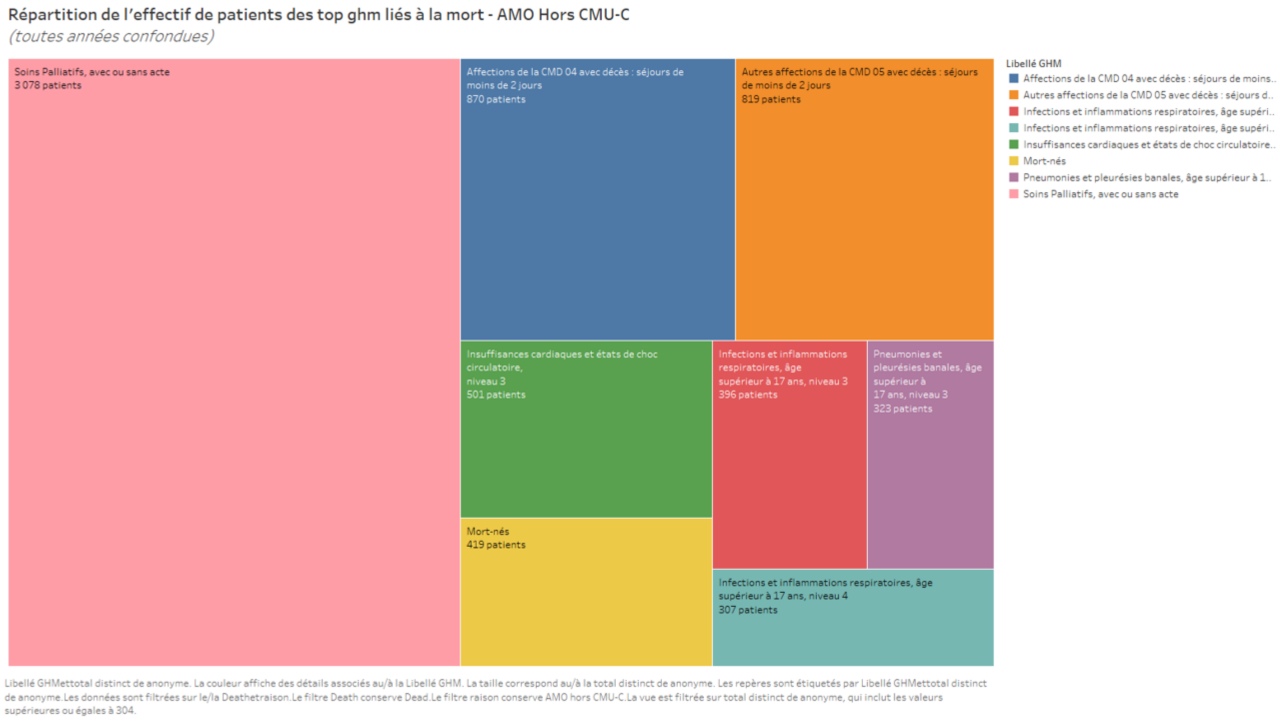


Figure 2.28: Death GHMs blocks distribution(patients, AMO, all years included)

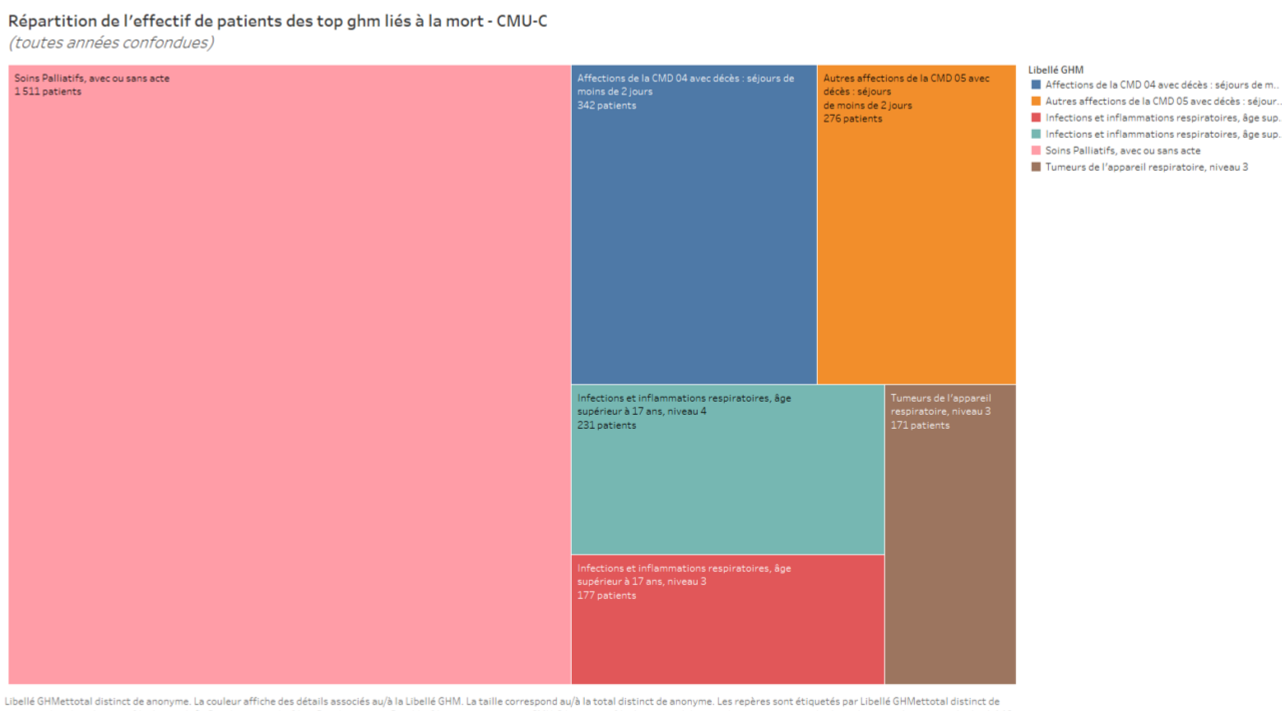


Figure 2.29: Death GHMs blocks distribution(patients, CMU-C, all years included)

2.2.5 Yearly evolution of patients contingents for the most represented GHMs groups

AMO systems features a great stability trought time of the top GHMs group patient counts. This is not the case for AME and CMU-C sytems that experienced a large drop of abortions. This large dwindle is not featured in the SUV case where abortion remains relatively stable over the 10 year period. Interstingly enough, we observe peaks for child deliveries without complications in 2013 and 2017 for CMU-C and in 2016 for SUV.

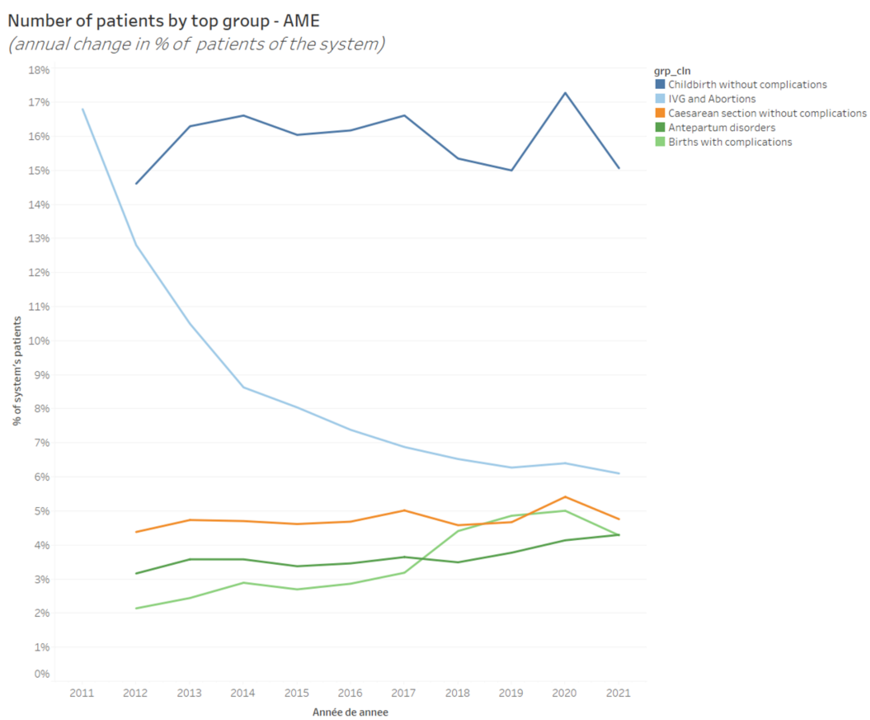


Figure 2.30: Yearly evolution of top GHMs groups (patients, AME)

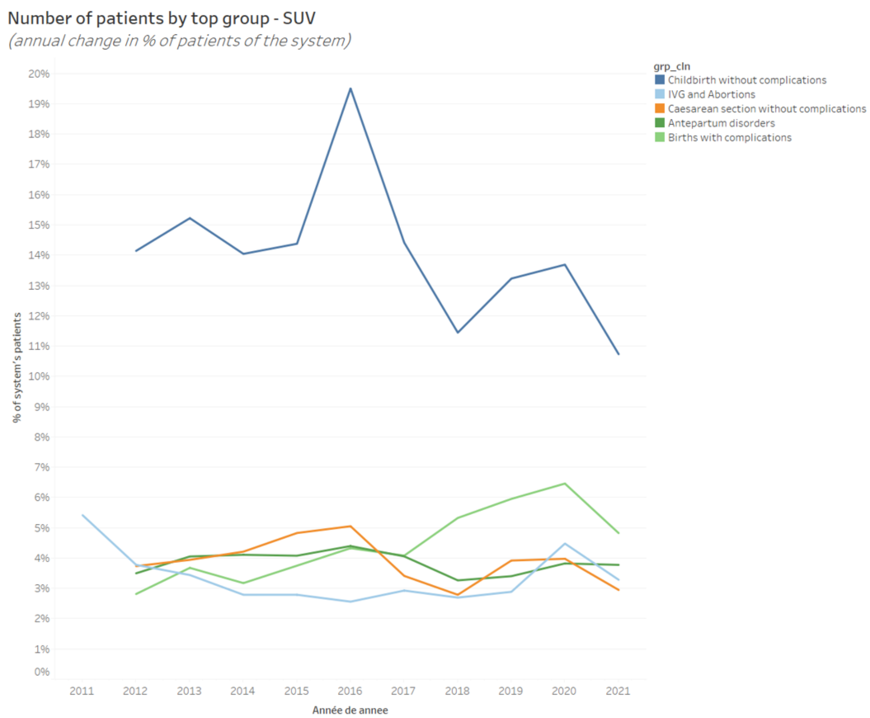


Figure 2.31: Yearly evolution of top GHMs groups (patients, SUV)

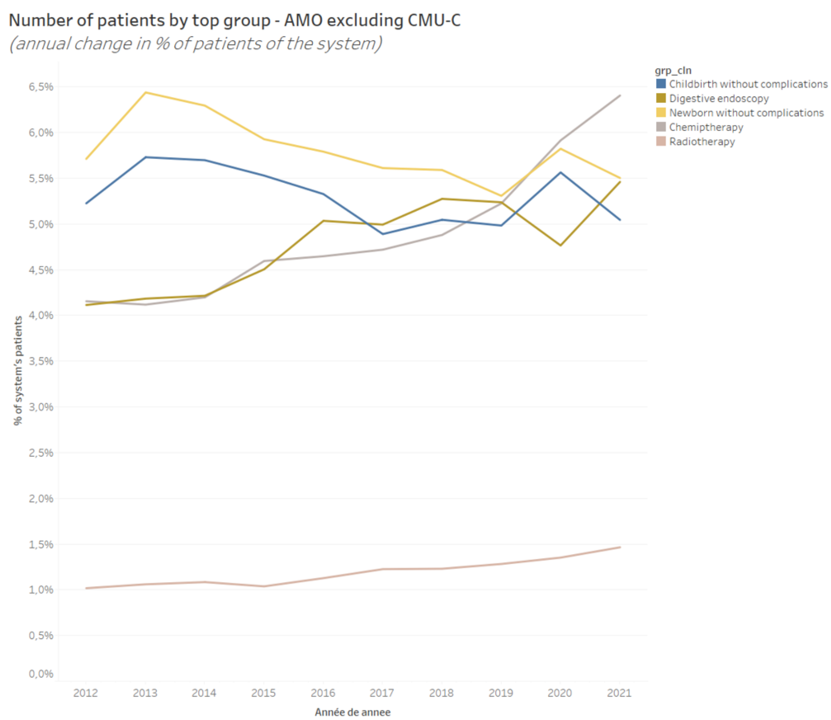


Figure 2.32: Yearly evolution of top GHMs groups (patients, AMO)

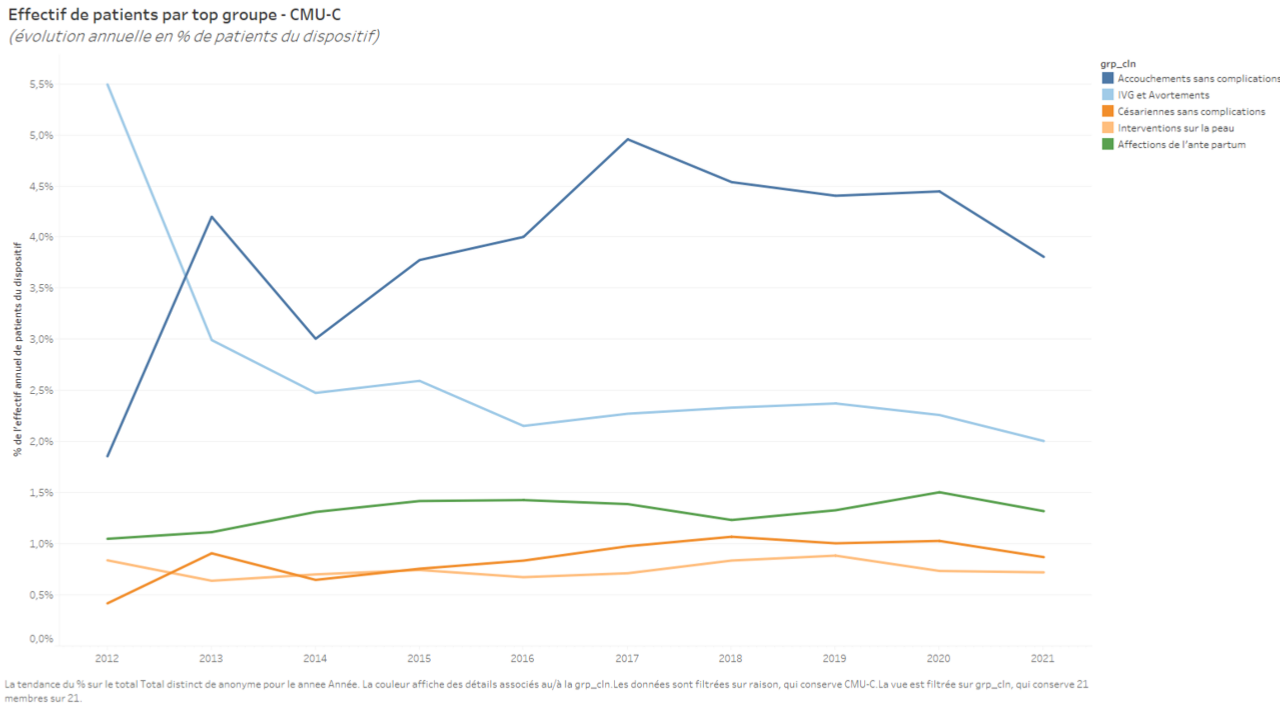


Figure 2.33: Yearly evolution of top GHMs groups (patients, CMU-C)

2.2.6 Critical Care Analysis

In this section we analyze the critical care differences between systems by leveraging two notions :

1. GHMs encoded with a severity gradation (makes up for about one third of all GHMs
2. Critical care supplement recorded in terms of days and used in stay cost computation

We will proceed by distinguishing a *static* analysis all year included and a *dynamic* one where we observe yearly evolution. We will finally focus on the actual GHMs blocks that participate most in critical care.

Static

We observe that SUV system has the most important proportion of level 4 severity stays (7%), CMU-C having the largest proportion of level 1 severity stays(24%). A chisquare test insures us that stays severity level is not statistically independent from systems.
Furthermore, SUV system has the largest proportion of stays with at least one supplement (7%) and the highest mean supplement (0.65 days) denoting an especially fragile population. The AMO base system is at the other end of the spectrum featuring only 0.3 days of mean supplement and 4.5‘% of its population with at least one supplement. AME case stands up as it is characterized by a small percentage of its population with supplement (4.5%) and a rather high mean supplement (0.45 days)

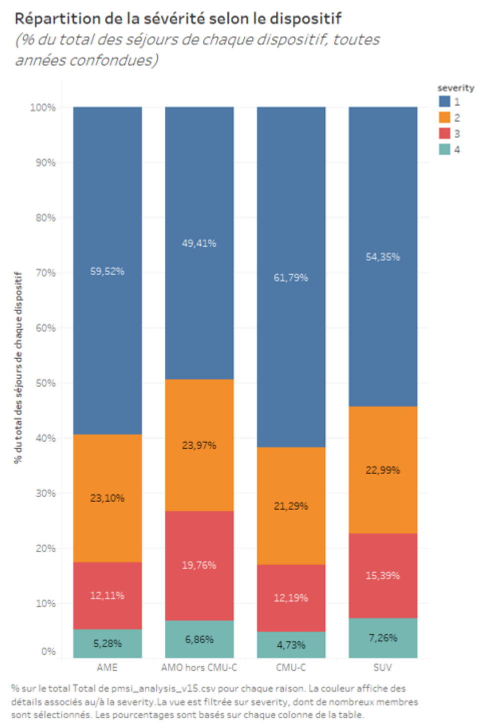


Figure 2.34: Severity distribution across systems (AYI)

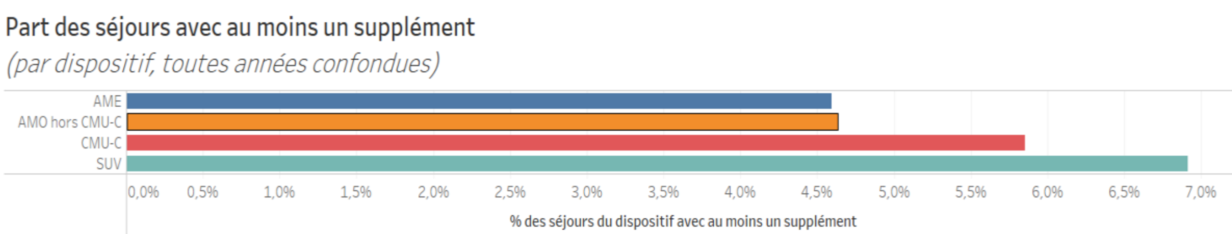


Figure 2.35: Proportion of stays with at least one supplement distribution (AS,AYI)

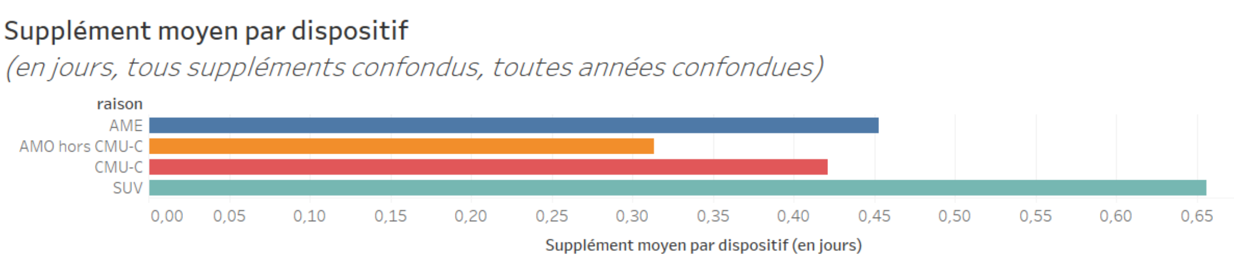


Figure 2.36: Mean supplement in terms of days distribution(AS,AYI)

Dynamic

In terms of severity levels distribution evolution we notice a similar pattern across all systems. A sensible decrease of the level 1 from 2012 to 2021 accompanied with mostly an sizeable increase of level 3 and 4 severities that nearly doubled over that time period.

Regarding supplement stays proportion evolution, we can distinguish two group of systems. AME and AMO that remained within the a relatively tight percentage range between 4.2% and 4.8%. SUV and CMU-C that both experienced large fluctuations. CMU-C exhibits a roughly steady increase from 5.3% to 6.2%.SUV's evolution is more chaotic, with a massive dwindle from 2015 to 2016 at 6.1%, it has overall increased from 6.2% to 6.9% in 2021 culminating at 7.4% in 2020.

Mean supplement evolution highlights 3 patterns. Stability with AMO's mean supplement remaining approximately stable through time. Increase within which we can distinguish the growth of CMU's mean from 0.38 to 0.45 days and the modest 0.04 days gain of AME featuring a peak at nearly O.5 days in 2015. And finally the high volatility evolution of SUV, exhibiting an important surge of 0.24 days culminating at 0.8 days from 2012 to 2013 and a sizeable decrease the following years leading to 0.6 days of mean supplement in 2021.

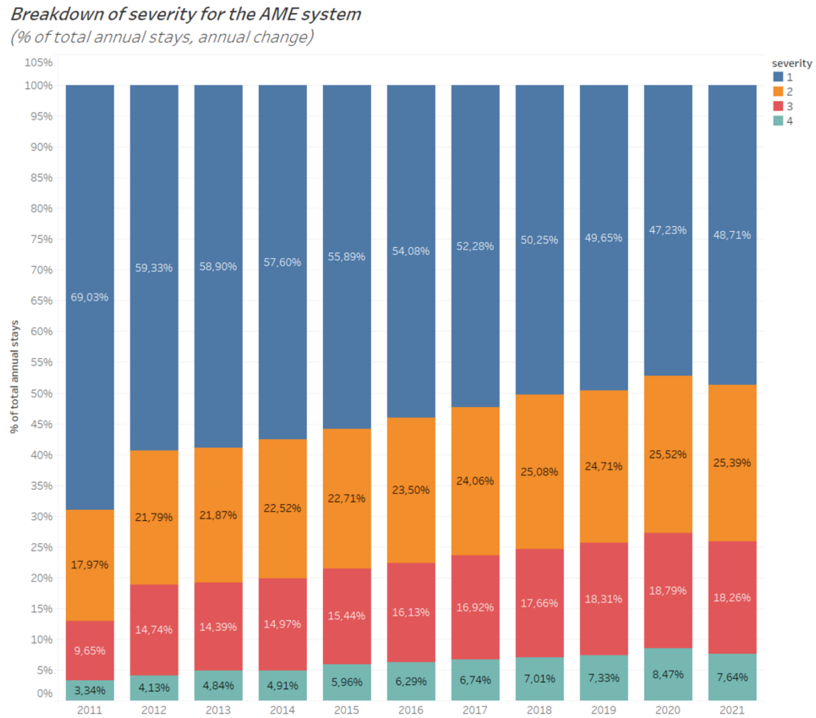


Figure 2.37: Severity distribution evolution (AME)

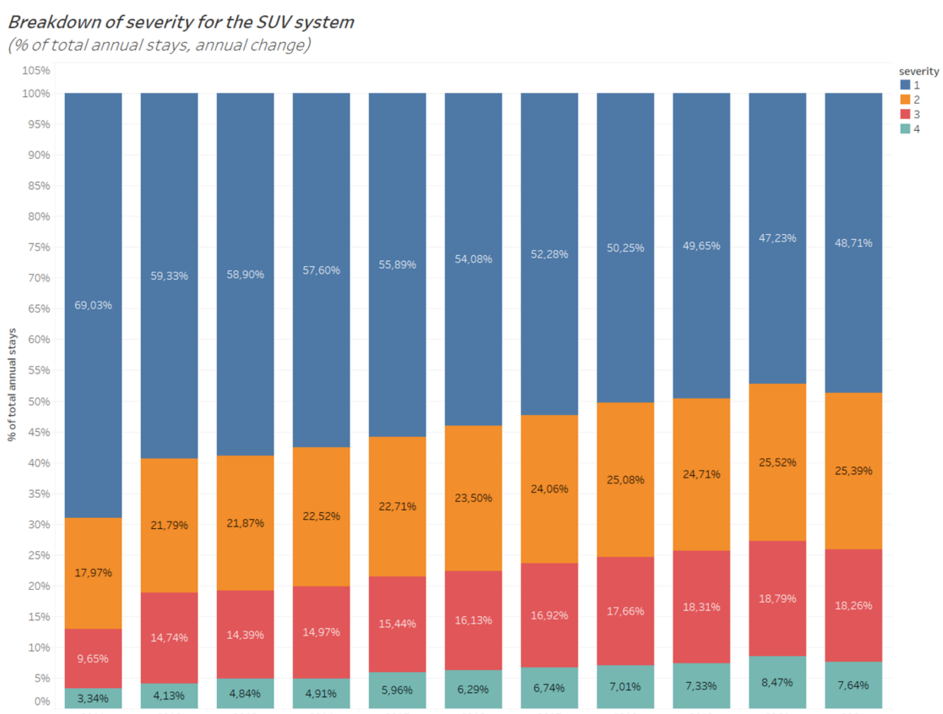


Figure 2.38: Severity distribution evolution (SUV)

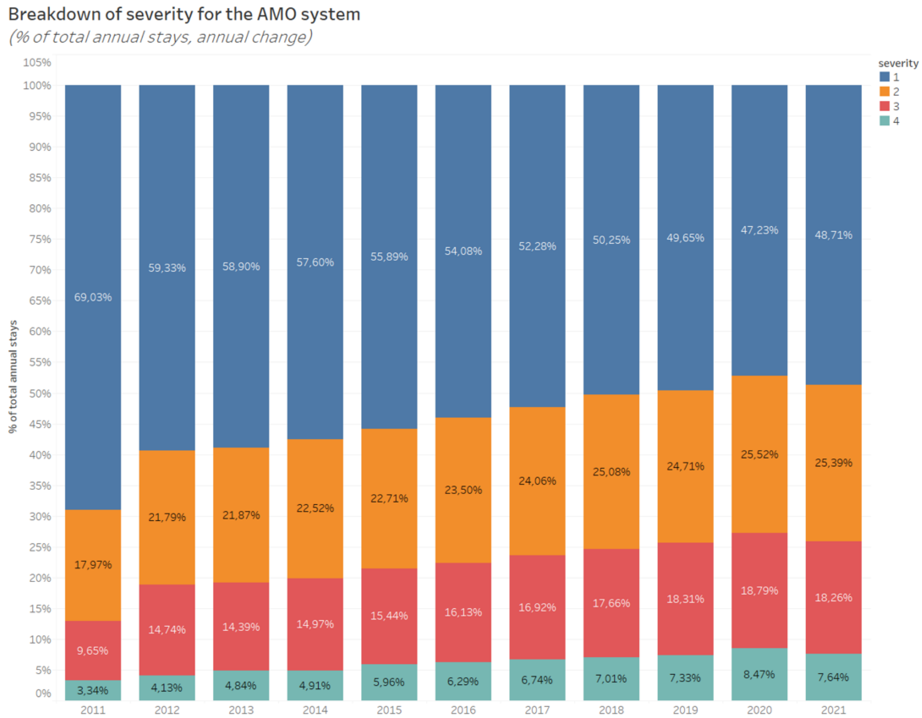


Figure 2.39: Severity distribution evolution (AMO)

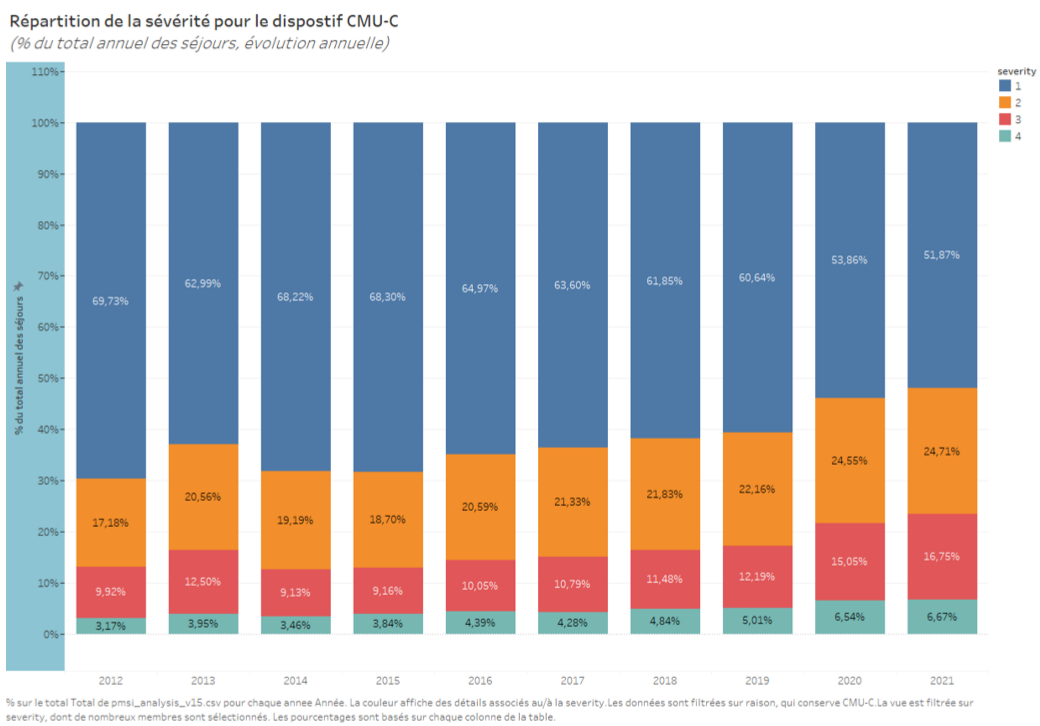


Figure 2.40: Severity distribution evolution (CMU)

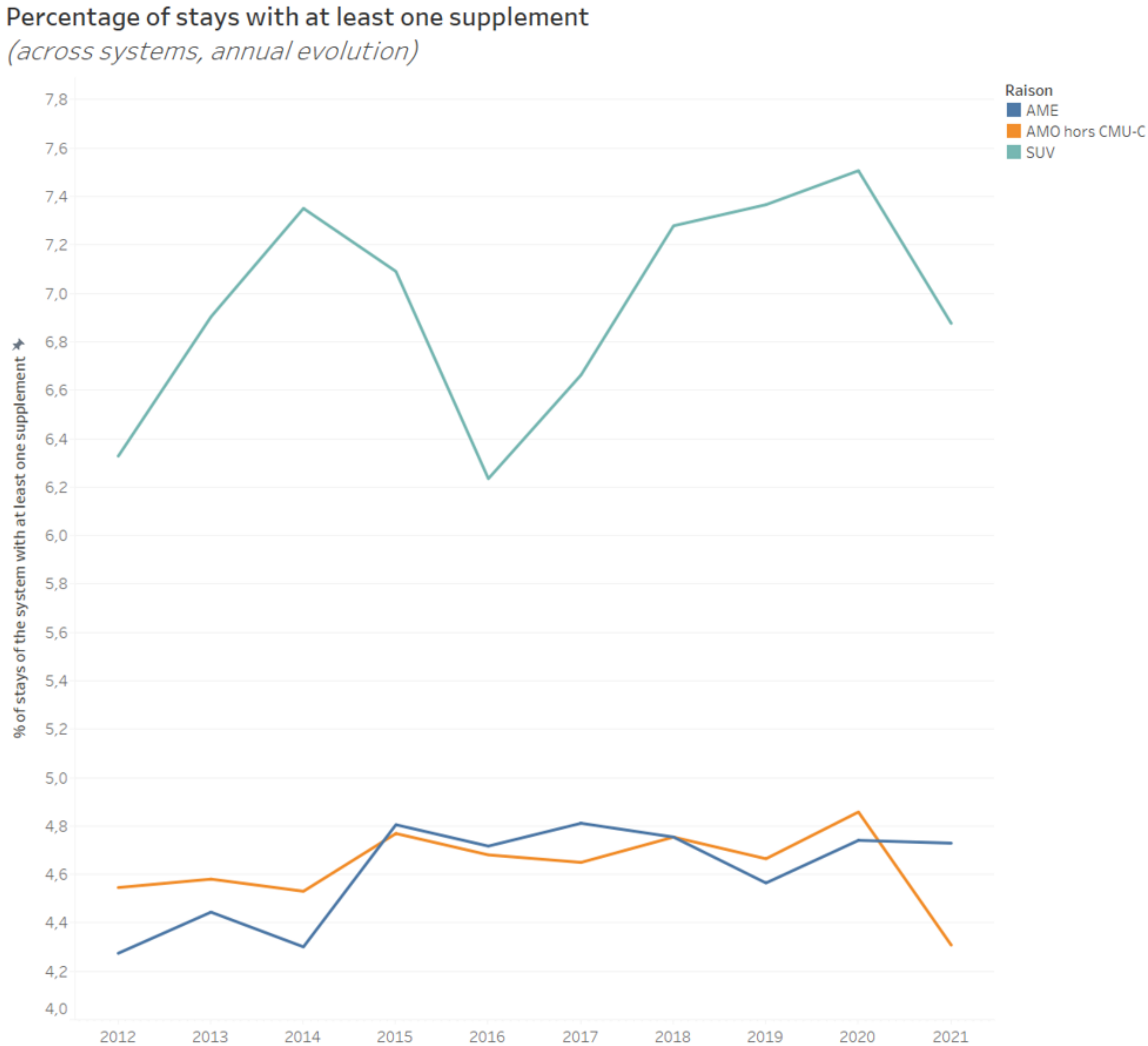


Figure 2.41: Supplement stays proportion evolution (AS)

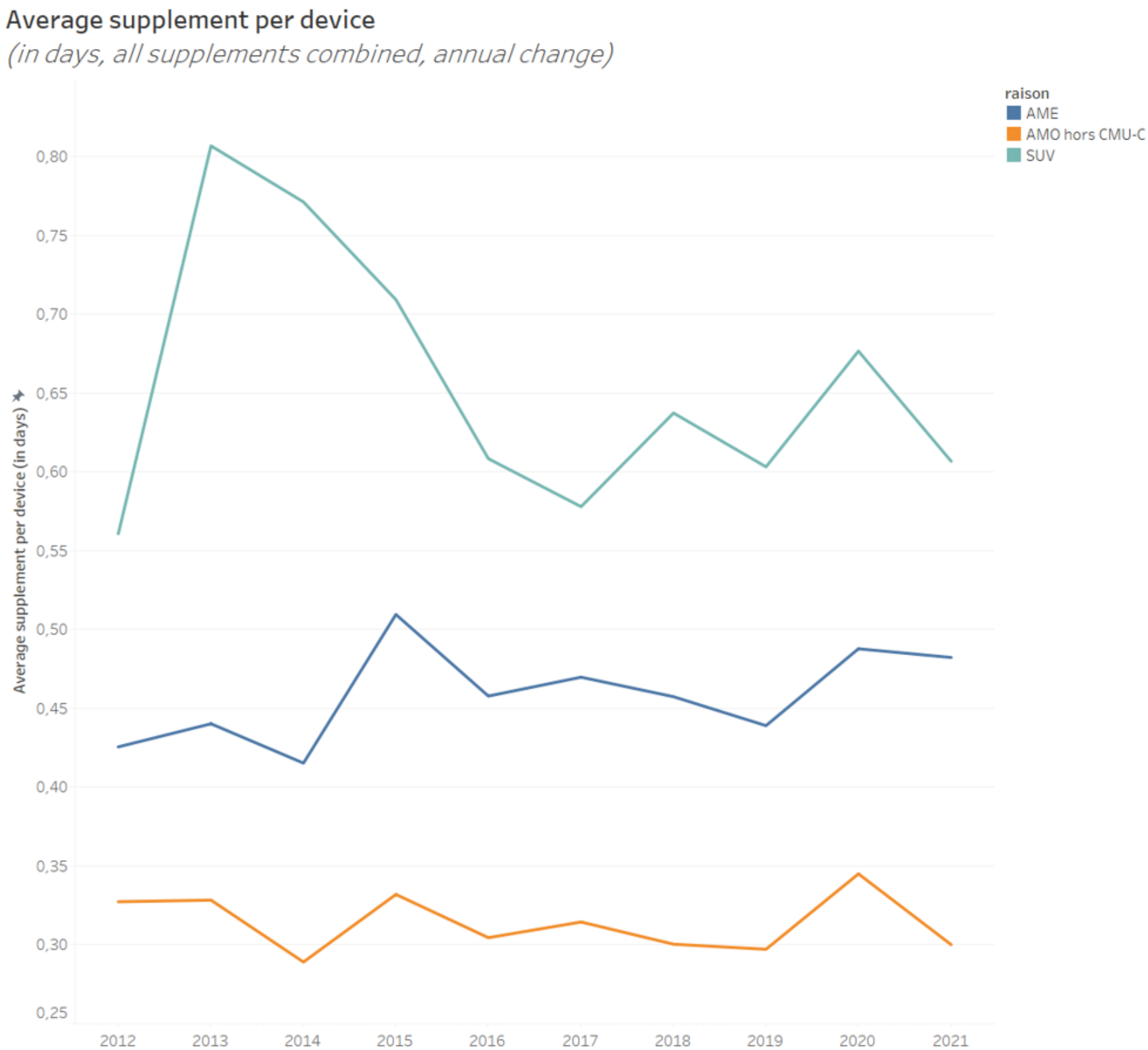


Figure 2.42: Mean supplement evolution (AS)

Critical care accross GHMs blocks and systems

The two following tables allow us to apprehend which are the GHMs blocks that are the most targeted by critical care. Analyzing the mean supplement across all the critical range, we notice a cross system pattern : neonatalogy has the highest mean supplement. When we further this analysis by not taking into account neonatalogy supplement.Doing so, we observe two cross systems GHMs block with high mean supplement : chest pain and caesarean section with complication. SUV system distinguishes itself by featuring two more GHMs blocks with high mean supplement : alcoholism and chemotherapy.

Supplément moyen par groupe selon le dispositif

(en jours, toutes années confondues)

grp_cln	AME	AMO hors CMU-C	CMU-C	SUV
Accouchements sans com..	0,00	0,00	0,00	0,00
IVG et Avortements	0,00	0,00	0,00	0,02
Césariennes sans complic..	0,00	0,00	0,01	0,00
Interventions sur la peau	0,00	0,00	0,00	0,00
Affections de l'ante partu..	0,00	0,00	0,00	0,00
Accouchements avec com..	0,03	0,02	0,02	0,04
Endoscopies digestives	0,00	0,00	0,00	0,01
Nouveau-nés sans compli..	7,39	0,76	1,56	9,97
Nouveau-nés avec complic..	14,34	4,37	7,27	16,81
Explorations et surveillan..	0,01	0,00	0,00	0,00
Douleurs thoraciques	0,42	0,35	0,41	0,27
Ethylisme	0,08	0,05	0,05	0,22
Diabète	0,01	0,01	0,01	0,01
Chimiothérapie	0,08	0,03	0,07	0,11
CMD 23	0,05	0,03	0,04	0,05
Interventions sur le crista..	0,00	0,00	0,00	0,00
Faux travail et menaces d'..	0,00	0,00	0,00	0,01
Douleurs abdominales	0,02	0,02	0,02	0,04
Césariennes avec complic..	0,28	0,22	0,32	0,24
Radiothérapies	0,00	0,00	0,00	0,00

supp moy.

0,00 16,81

Moyenne de supp représenté selon raison vs. grp_cln. La couleur met en avant le/la moyenne de supp. Les repères sont étiquetés par moyenne de supp.La vue est filtrée sur grp_cln, qui exclut Autres.

Figure 2.43: Mean supplements across GHMs blocks and systems(AYI)

2.2.7 Cost analysis

In this section, we break up the cost analysis in two usual groups : *static* and *dynamic*. Whithin the *static* analysis, in addition to total cost and mean cost description , we will project total cost on the granular GHMs blocks to determine which are the most financially prominent GHMs across systems.

Supplément moyen par groupe selon le dispositif

(en jours, toutes années confondues - suppléments de néonatalogie exclus)

grp_cln	AME	AMO hors CMU-C	CMU-C	SUV
Accouchements sans com..	0,0009	0,0007	0,0004	0,0001
IVG et Avortements	0,0024	0,0001	0,0034	0,0154
Césariennes sans complic..	0,0041	0,0023	0,0084	0,0024
Interventions sur la peau	0,0019	0,0000	0,0008	0,0000
Affections de l'ante partu..	0,0010	0,0012	0,0014	0,0030
Accouchements avec com..	0,0255	0,0181	0,0247	0,0386
Endoscopies digestives	0,0002	0,0007	0,0016	0,0146
Nouveau-nés sans compli..	0,0058	0,0002	0,0007	0,0000
Nouveau-nés avec complic..	0,0868	0,0381	0,0650	0,0090
Explorations et surveillan..	0,0044	0,0009	0,0003	0,0000
Douleurs thoraciques	0,4218	0,3505	0,4070	0,2697
Ethylisme	0,0789	0,0512	0,0507	0,2167
Diabète	0,0121	0,0140	0,0120	0,0111
Chimiothérapie	0,0802	0,0279	0,0652	0,1134
CMD 23	0,0242	0,0184	0,0270	0,0176
Interventions sur le crista..	0,0002	0,0005	0,0008	0,0000
Faux travail et menaces d'..	0,0012	0,0000	0,0034	0,0077
Douleurs abdominales	0,0078	0,0075	0,0091	0,0297
Césariennes avec complic..	0,2777	0,2188	0,3158	0,2402
Radiothérapies	0,0000	0,0000	0,0000	0,0000

supp hors nn moy.
0,0000 0,4218

Moyenne de supp hors nn représenté selon raison vs. grp_cln. La couleur met en avant le/la moyenne de supp hors nn. Les repères sont étiquetés par moyenne de supp hors nn.La vue est filtrée sur grp_cln, qui exclut Autres.

Figure 2.44: Mean supplements across GHMs blocks and systems(AYI, neonatalogy exluded)

Static

Total stays cost across systems highlights AME system as the second most expensive system costing 2.5 billion euros from 2011 to 2021 just marginally below AMO. This is due to the very large number of stays compared to the patient count resulting from GHMs that requires reoccurring stays (mainly hemodialysis and all GHMs in *CMD Séances*

Regarding mean stay cost, there are roughly the identical for AME, AMO and CMU-C at about 2500 euros. SUV stands out with a 1100 euros premium at 3600 euros mean stay cost. This difference can be thought of as illustrating the fragility of SUV's population.

In terms of big GHM blocks contribution to the total cost of each system, we notice a clear divide between the migrant target systems that have obstetrics/genecology making up the majority of their total cost with 60% for AME and up to 77% for SUV. CMU-C's total cost is splitted evenly across blocks whereas Oncology is predominant in AMO's total cost at about 60%. These observations are consistant with the fact that AMO's age distribution is skewed towards more senior people whereas SUV's and AME's is skewed towards a younger population.

The last chart just details this picture by underlyning the fact that most of AMO's oncology cost is due to chemotherapy and most of SUV's and AME's obstetrics/gynecology cost is made up by regular childbirths and caesarean section without complications.

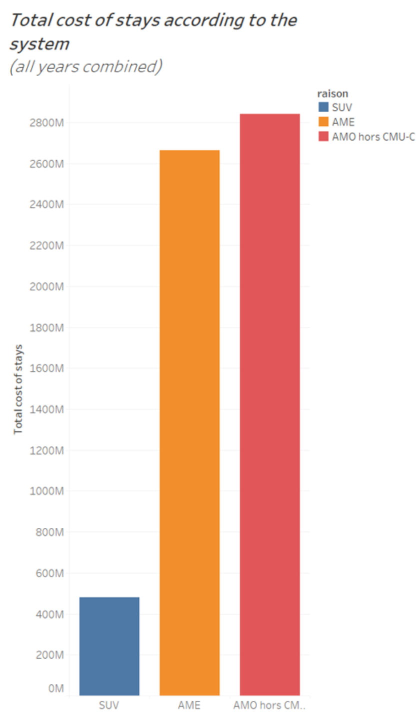


Figure 2.45: Total cost of stays (AC, AYI)

Dynamic

Total cost evolution is characterized by an increasing pattern across all systems. SUV went from about 20M euros in 2011 to over 40M in 2021. AME doubles its total cost from 120m euros to around 270M euros in 2021. AMO's envelope slightly whereas CMU-C's exhibits a peculiar evolution with a massive 180M euros drop from 2013 to 2014 and steady increase culminating at 300M euros in 2021.

Total cost yearly evolution is characterized by an increasing pattern across all systems. SUV went from about 20M euros in 2011 to over 40M in 2021. AME doubles its total

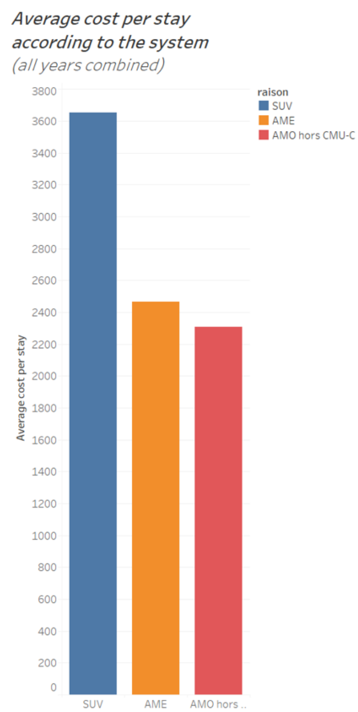


Figure 2.46: Mean cost of stays (AC, AYI)

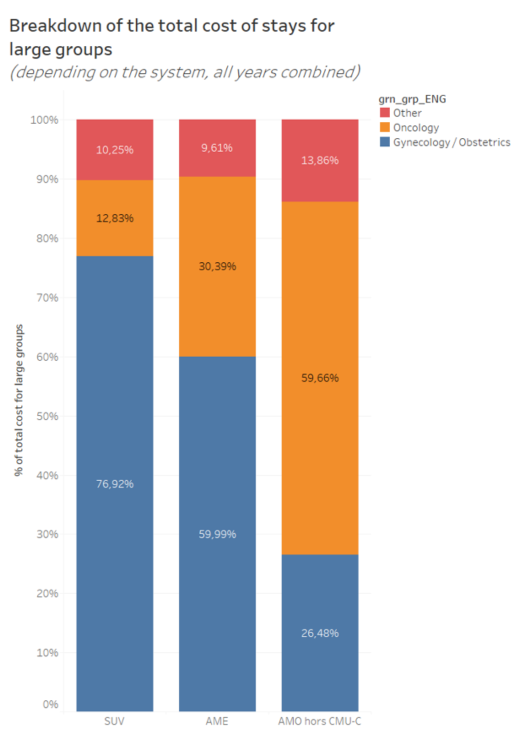


Figure 2.47: Total cost of the big GHM blocks (in term of stays, AC, AYI)

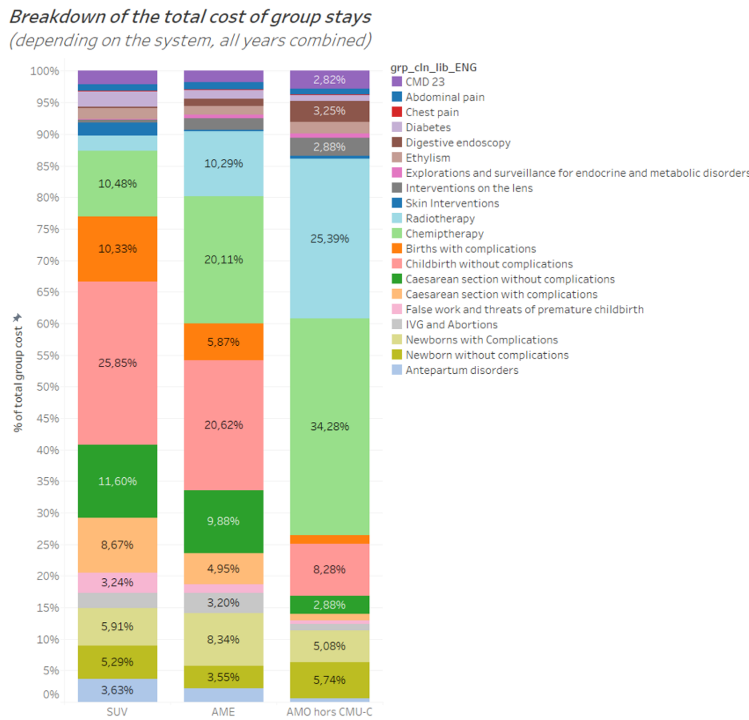


Figure 2.48: Total cost of the granular GHM blocks (in term of stays, AC, AYI)

cost from 120m euros to around 270M euros in 2021. AMO's envelope slightly whereas CMU-C's exhibits a peculiar evolution with a massive 180M euros drop from 2013 to 2014 and steady increase culminating at 300M euros in 2021.

Patient mean cost is relatively stable during the time period for all systems, with a convergence at 5000 euros per patient in 2021 for SUV that dwindled, AME and AMO. CMU-C lies behind and evolved from 4000 euros in 2012 to 4500 euros in 2021.

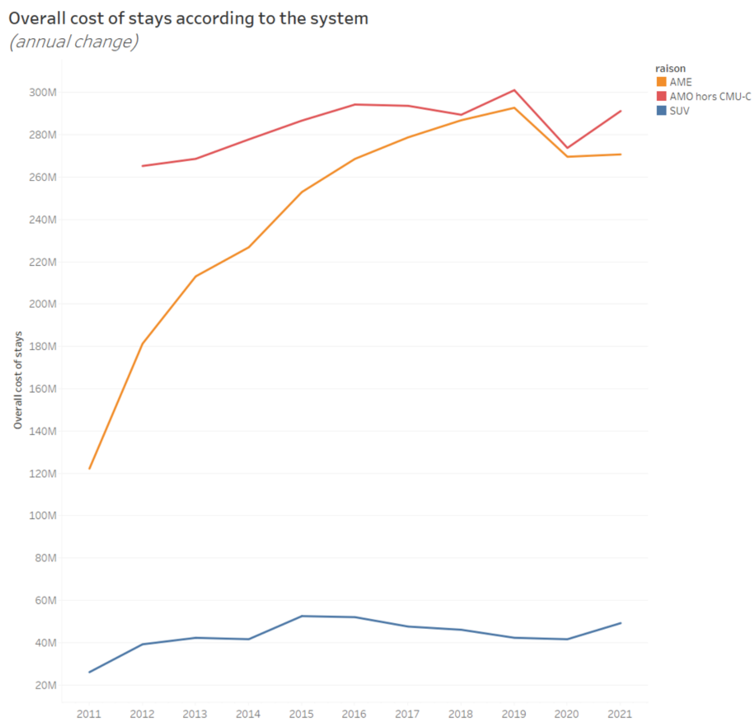


Figure 2.49: Total cost evolution (AC)

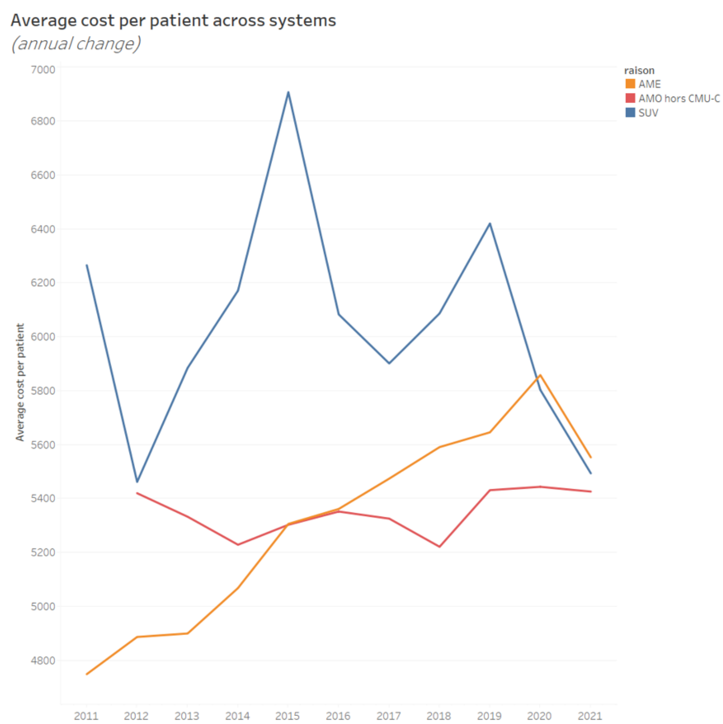


Figure 2.50: Mean cost evolution (AC)

2.3 *Séances* GHM focus

This section explores the CMD *Séances* pertaining to reoccurring care. Our analysis will be broken in two parts :

1. Understanding to what extend reoccurring stays differ from a system to another by scrutinizing the mean number of stays per patients as well as the mean duration of this stays across systems

2. Characterizing the total and mean cost of hemodialysis across systems and age class

Mean number of stays and mean duration of reoccurring stays across systems

AME stands out as being an outlier when it comes to the mean number of stays(mns). This system has the highest mns for every single subgroups of *CMD Séances*, hemodialisys contrasting the most with 86 mns per patient in the system. This underlines an important pattern in terms of population composition and care typology.
Regarding the mean stay duration(msd), AME's patients seems to have rather short stays. SUV exhibits the longest msd for chemotherapy at 0.76 days, CMU-C for hemodialysis at 0.6 days more than double that of AME.

Breakdown of the *CMD Séance* on the number of patients and stays, for each system
(all years combined)

	SUV	AME	AMO hors CMU-C
Hemodialysis	796 (P) 19 422 (S) 24,40(SM)	1 981 (P) 171 032 (S) 86,34(SM)	1 611 (P) 107 938 (S) 67,00(SM)
Chemotherapy	1 695 (P) 5 747 (S) 3,39(SM)	13 577 (P) 99 813 (S) 7,35(SM)	23 741 (P) 174 559 (S) 7,35(SM)
Radiotherapy	126 (P) 1 706 (S) 13,54(SM)	2 887 (P) 58 779 (S) 20,36(SM)	6 984 (P) 130 188 (S) 18,64(SM)
Other	232 (P) 606 (S) 2,61(SM)	2 037 (P) 9 533 (S) 4,68(SM)	4 275 (P) 20 027 (S) 4,68(SM)

2,61 86,34

Figure 2.51: CMD *Seances* mean number of stays (AC,AYI)

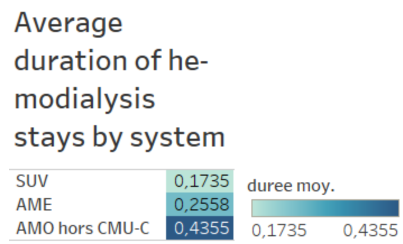


Figure 2.52: Hemodialysis mean stay duration (AC,AYI)

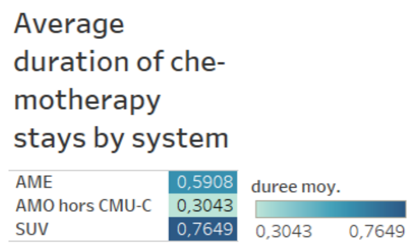


Figure 2.53: Chemotherapy mean stay duration (AC,AYI)

Hemodialysis cost analysis

AME's total cost of hemodialysis illustrates the fact that this GHM is a defining factor for the population of this system. Despite having a lower contingent of patients, AME's cost is higher than the base system by a margin of 20M euros all years included. For the two other systems, the expense envelope is consistent with their population size.
When we focus on the mean cost (mc) of this GHM across age, we notice a logical increase of mc as the population gets older that is featured by all systems. The highest mc are surprisingly observed on the two general population systems, AMO from 0 to 35 year old and CMU-C from 36 to 89 year old.

Chapter 3

Comparative analysis between social systems and the base system

In this section, we seek to quantify differences between systems through the computation of indicators pertaining to stays duration, critical care duration and overall stay cost. The main idea is to compare each of the social systems(SUV, AME, CMU-C) with base system (AMO) leveraging the notion of precariousness premium.

In other words, we aim at measuring how much more do social systems patients cost

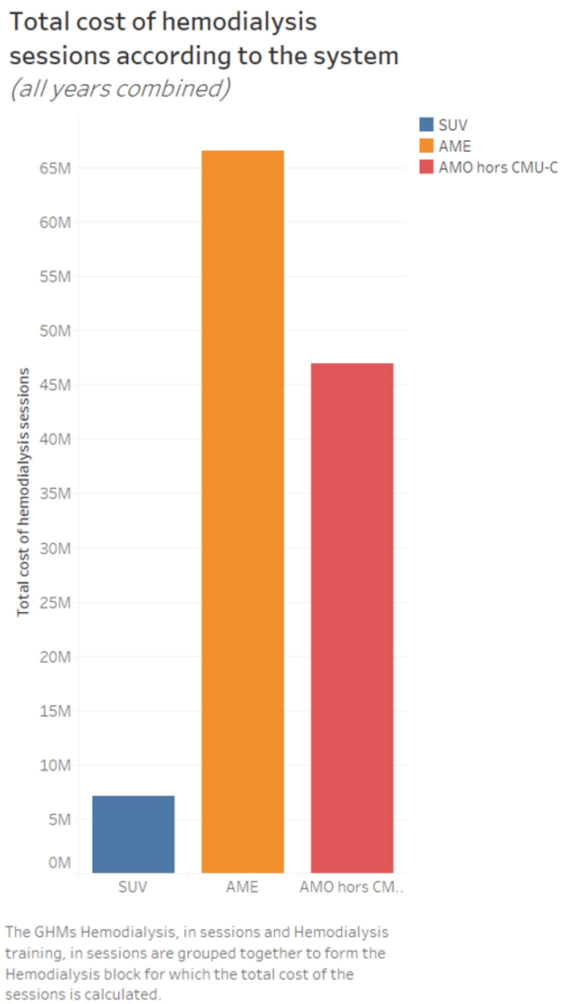
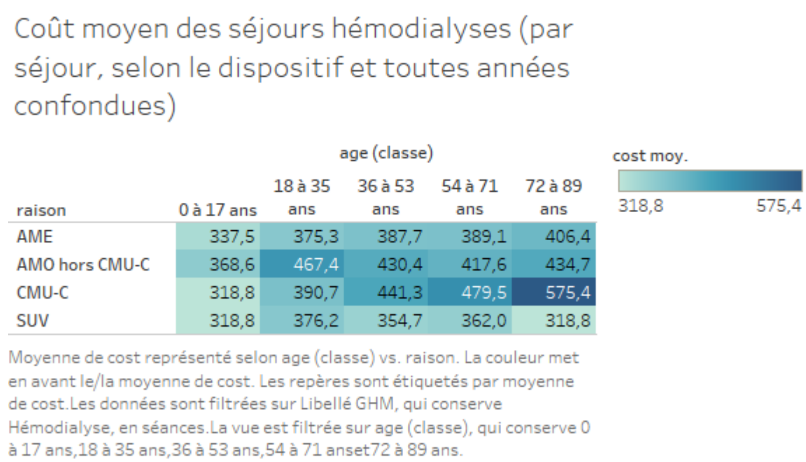


Figure 2.54: CMD *Seances* mean number of stays (AC,AYI)



	age (classe)				
raison	0 à 17 ans	18 à 35 ans	36 à 53 ans	54 à 71 ans	72 à 89 ans
AME	337,5	375,3	387,7	389,1	406,4
AMO hors CMU-C	368,6	467,4	430,4	417,6	434,7
CMU-C	318,8	390,7	441,3	479,5	575,4
SUV	318,8	376,2	354,7	362,0	318,8

Figure 2.55: Hemodialysis mean stay duration (AC,AYI)

compared to the base system, how much more important their stays and critical care needs are as opposed to the base system. In addition to global mean difference across these indicators, we go further and propose a more sophisticated methodology. It consists in working on a GHM per GHM basis in order to qualify these differences for additional information regarding the clinical profile of patients. For each of the 2300 GHMs, we randomly match stays from the precarious system with stays from the base system on a 1:1 scheme. We then computed the differences (assuming social systems have higher values, and thus on the left part of the subtraction) and the associated 95% confidence intervals. We select a sub-sample of GHM where the global average *premium* is statistically significant by performing a Welch's t-test.

3.1 Stays duration analysis

The number of GHMs for which the mean stay duration difference is statistically different is the following

1. 470 GHMs for SUV vs AMO
2. 453 GHMs for AME vs AMO
3. 212 GHMs for CMU-C vs AMO

This ranking clearly alludes to a gradation with regards to the precariousness of patient as opposed to the base system. The more targeted and specific the system, the more there is statistically significant differences with the general population.

In more details, we see that the most significant GHMs in terms of both mean difference in stay duration and confidence intervals across all social systems are related to surgical interventions (hip, leg, knee). For instance for SUV, we have an average *overduration* of stays of more than 35 days, ranging from about 15 to 95 days with a 95% confidence. An other interesting fact is the typical over representation of skin related condition GHMs for SUV system.

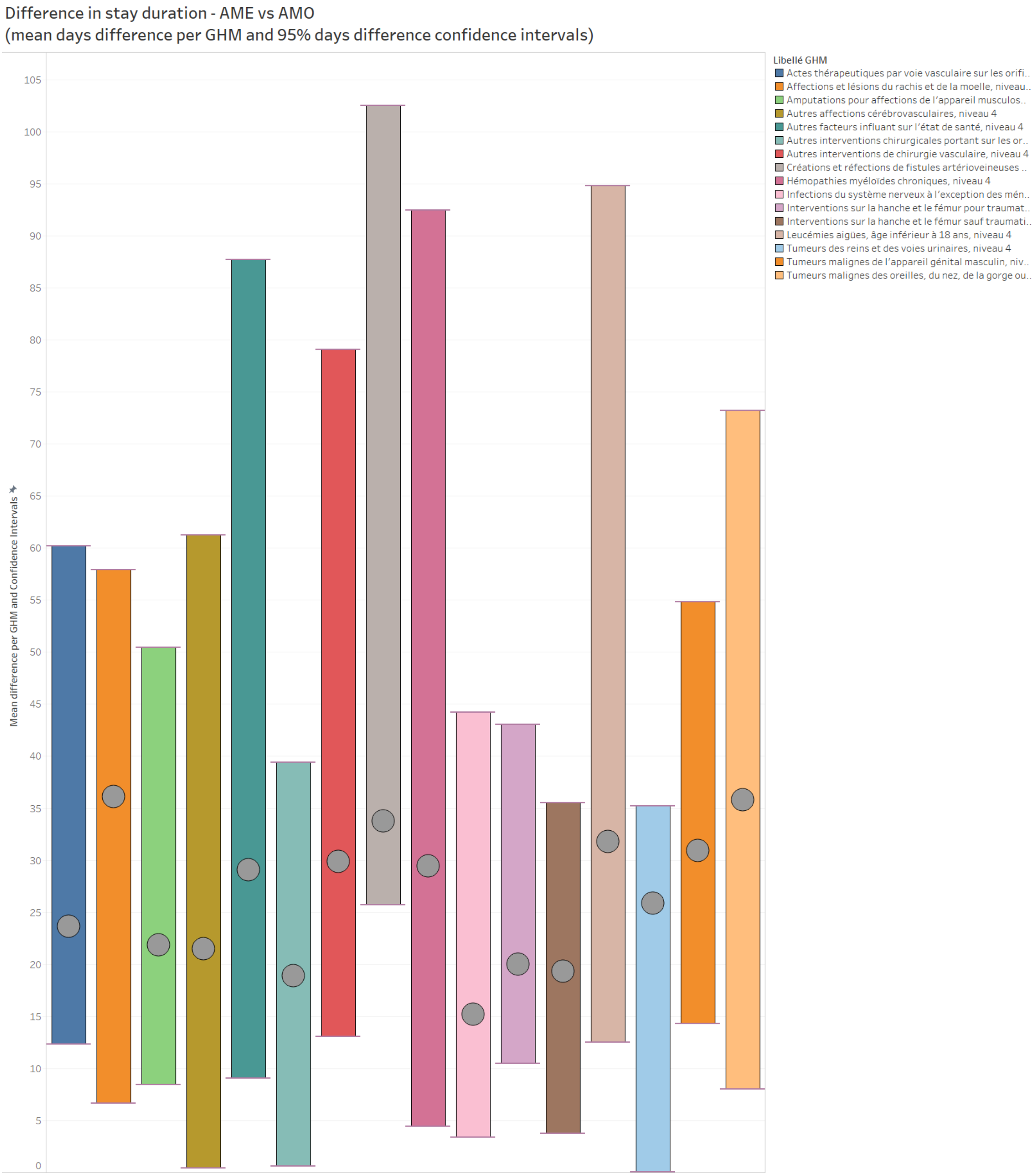


Figure 3.1: Difference in stay duration - AME vs AMO (AYI)

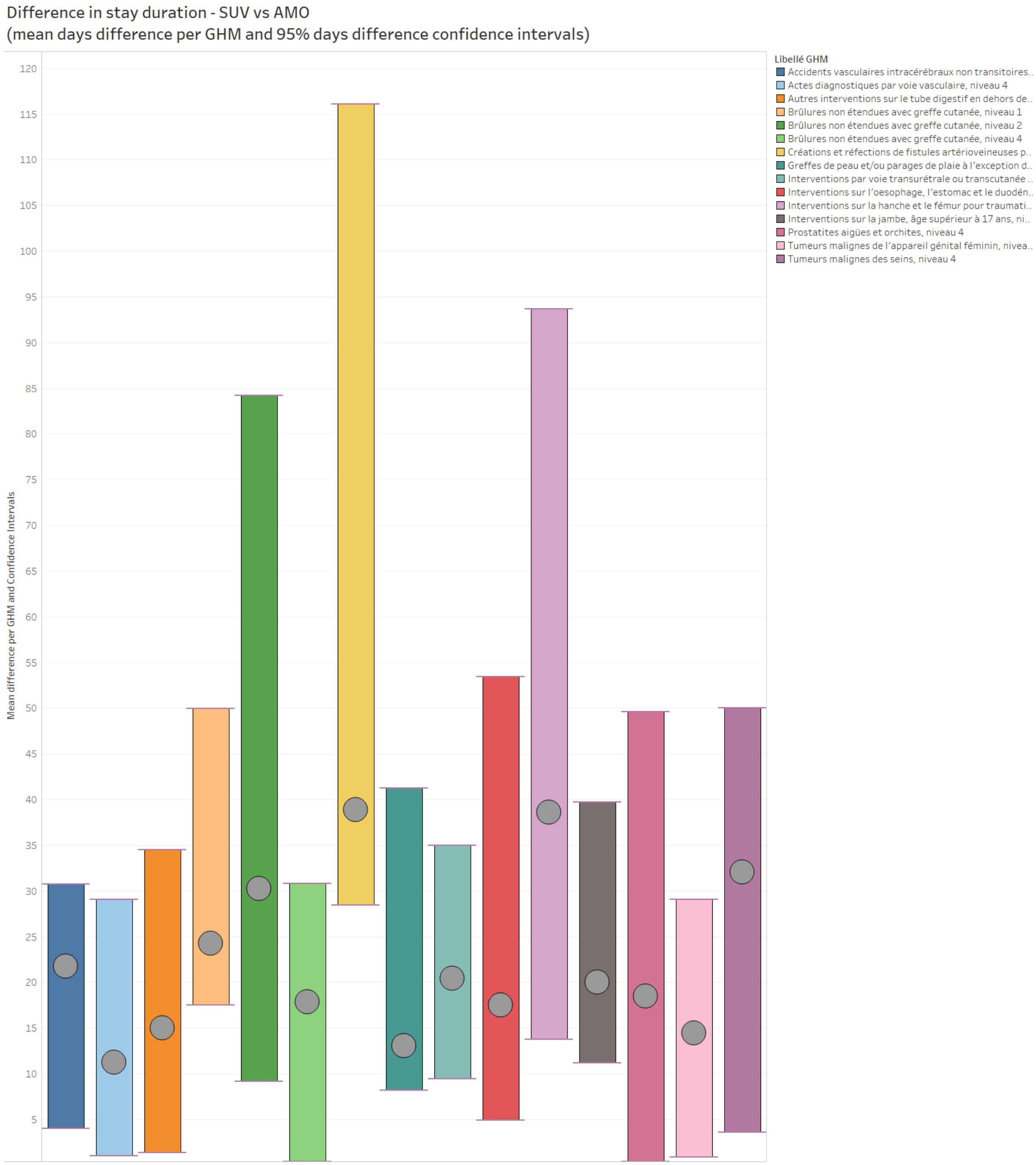


Figure 3.2: Difference in stay duration - SUV vs AMO (AYI)

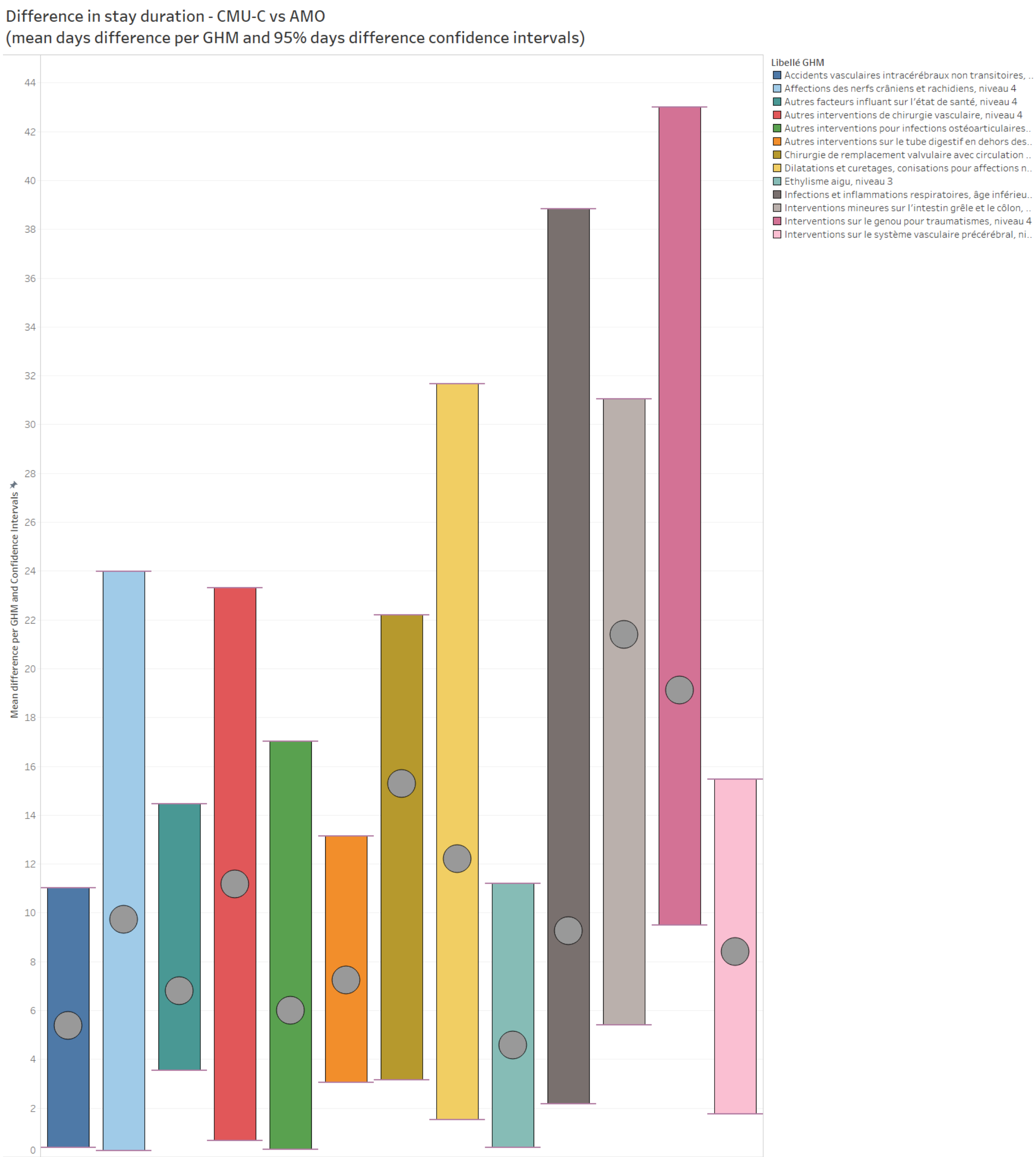


Figure 3.3: Difference in stay duration - CMU-C vs AMO (AYI)

3.2 Critical care duration analysis

By critical care duration we refer to all the supplement (in days) found in the PMSI that relate to some kind of complication : *intensive care units*, *continuous monitoring* etc. These have all been aggregated to create an indicator of critical care duration.

The number of GHMs for which the mean critical care duration difference is statistically different is the following

1. 63 GHMs for SUV vs AMO
2. 160 GHMs for AME vs AMO
3. 146 GHMs for CMU-C vs AMO

This ranking is not akin with the previous intuition. AME has the highest number of statistically significant differences, followed by CMU-C, SUV being largely behind. This suggests that even thought SUV patients tend to have longer stays comparatively with other social systems, this is not due to the importance of critical care. It may reveal a structural bias in the way the stays are recorded in the public care IT systems.

Leveraging the charts, we can observe that the GHMs present for CMU-C are more fragmented than SUV and AME. The presence of acute level 4 alcoholism is particularly striking, with an average *overduration* of critical care 7 days ranging from less than a day to 21 days with a 95% confidence. We find acute leukemia GHM significant for both SUV and AME, with a greater mean and *overduration* range for SUV. The GHM structure is globally similar between these two systems as it relates especially to cancers and vascular interventions.

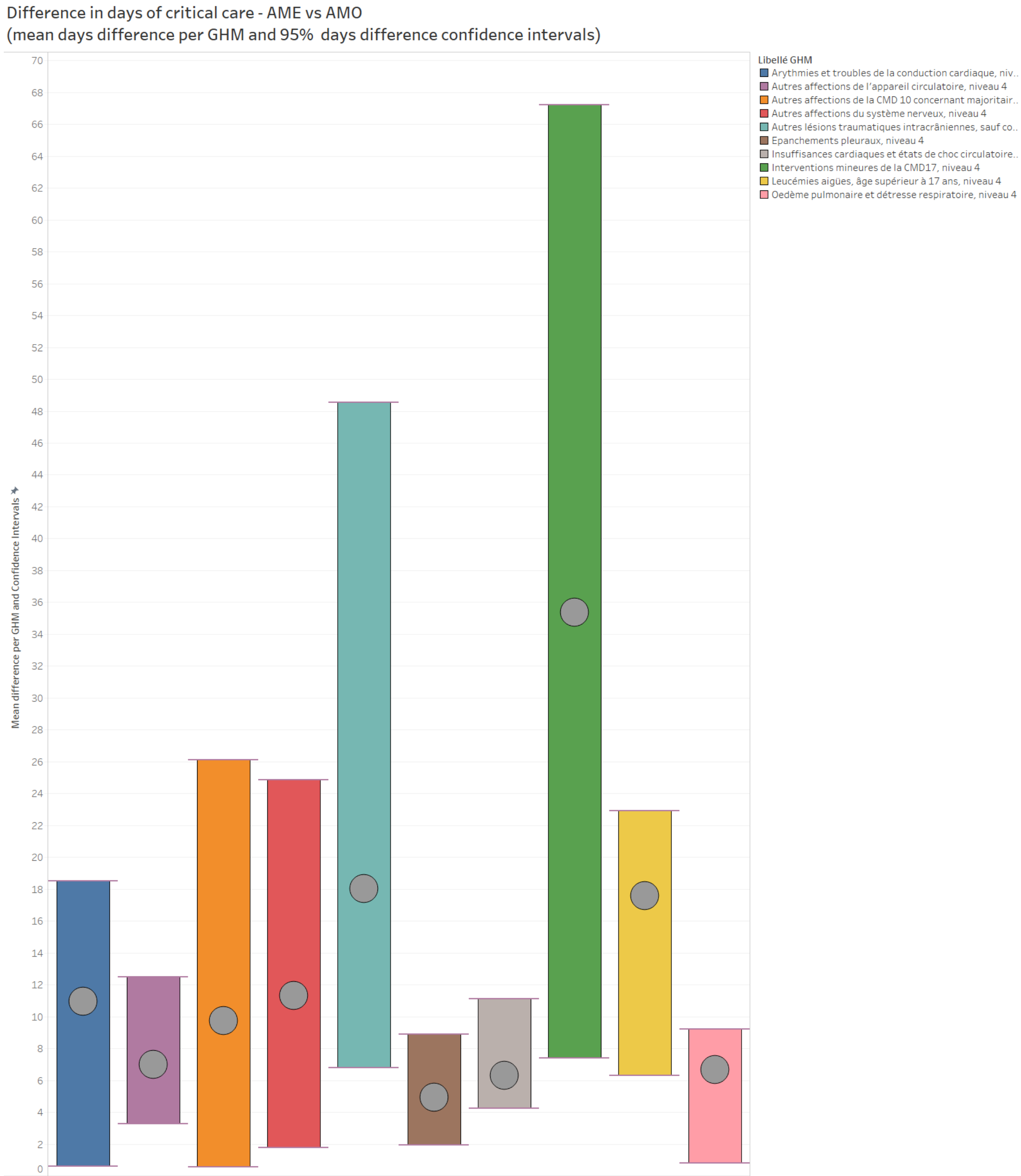


Figure 3.4: Difference in critical care duration - AME vs AMO (AYI)

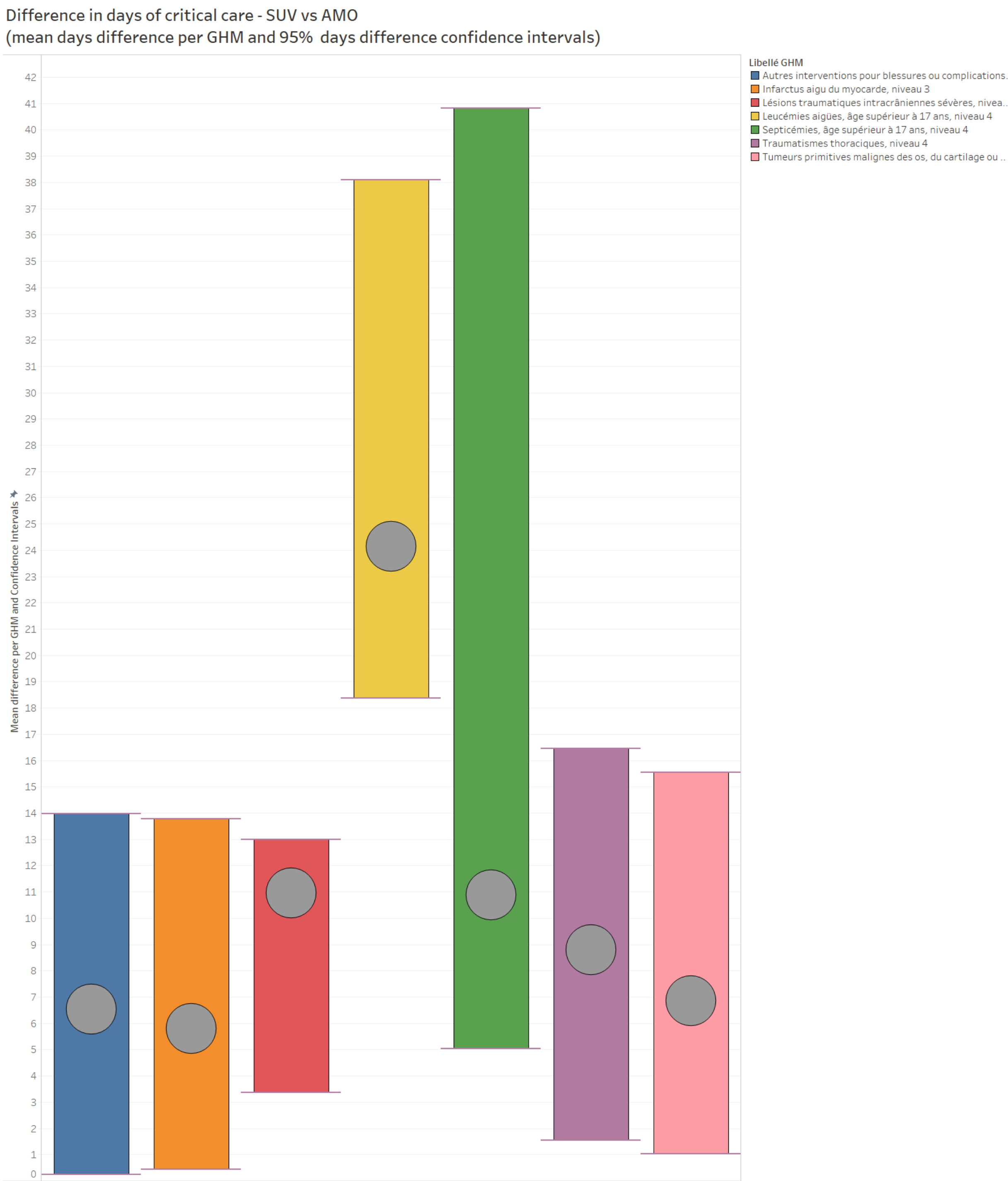


Figure 3.5: Difference in critical care duration - SUV vs AMO (AYI)

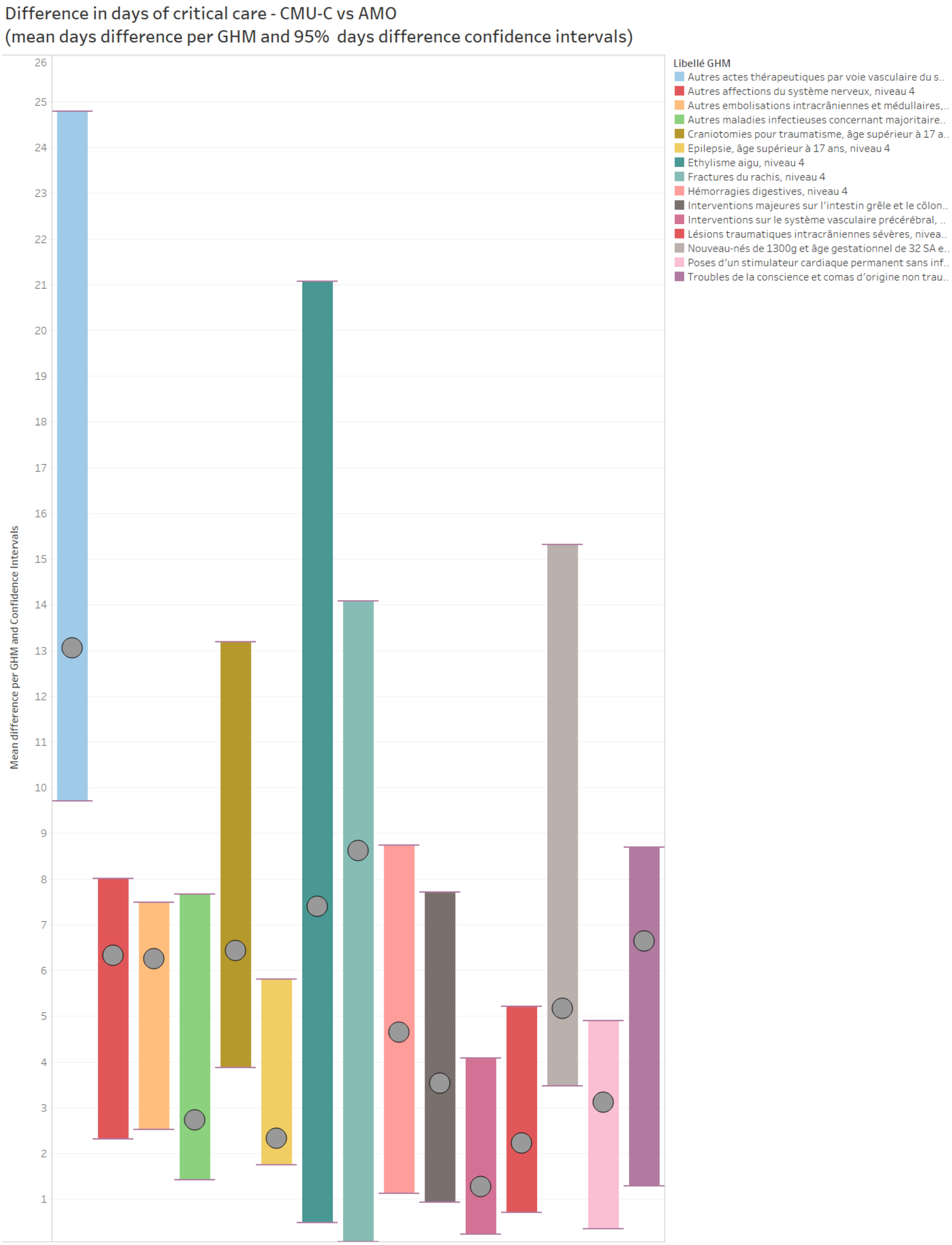


Figure 3.6: Difference in critical care duration - CMU-C vs AMO (AYI)

3.3 Stays Cost analysis

Stays cost computation being largely affected by stay duration, we expect to find largely similar results that the previous analysis.

The number of GHMs for which the mean stay cost difference is statistically different is the following

1. 460 GHMs for SUV vs AMO
2. 476 GHMs for AME vs AMO
3. 203 GHMs for CMU-C vs AMO

This is akin to the observation made for the differences in stays duration, both in term of ranking than in term of volume of statistically significant GHMs.

Going into the details provided by the charts, we can see that the GHMs present in each systems represent both what we observed for *overduration* of stays and critical care. For instance we see the presence of both leukemia and leg and hip surgical interventions for AME. This pattern of consolidation is repeated for SUV and CMU-C. Acute leukemia in the SUV overcost chart pictures the largest difference observed with the base system, with an average premium of about 30 000 Euros ranging from 17 000 euros to up 46 000 euros with a 95% confidence.

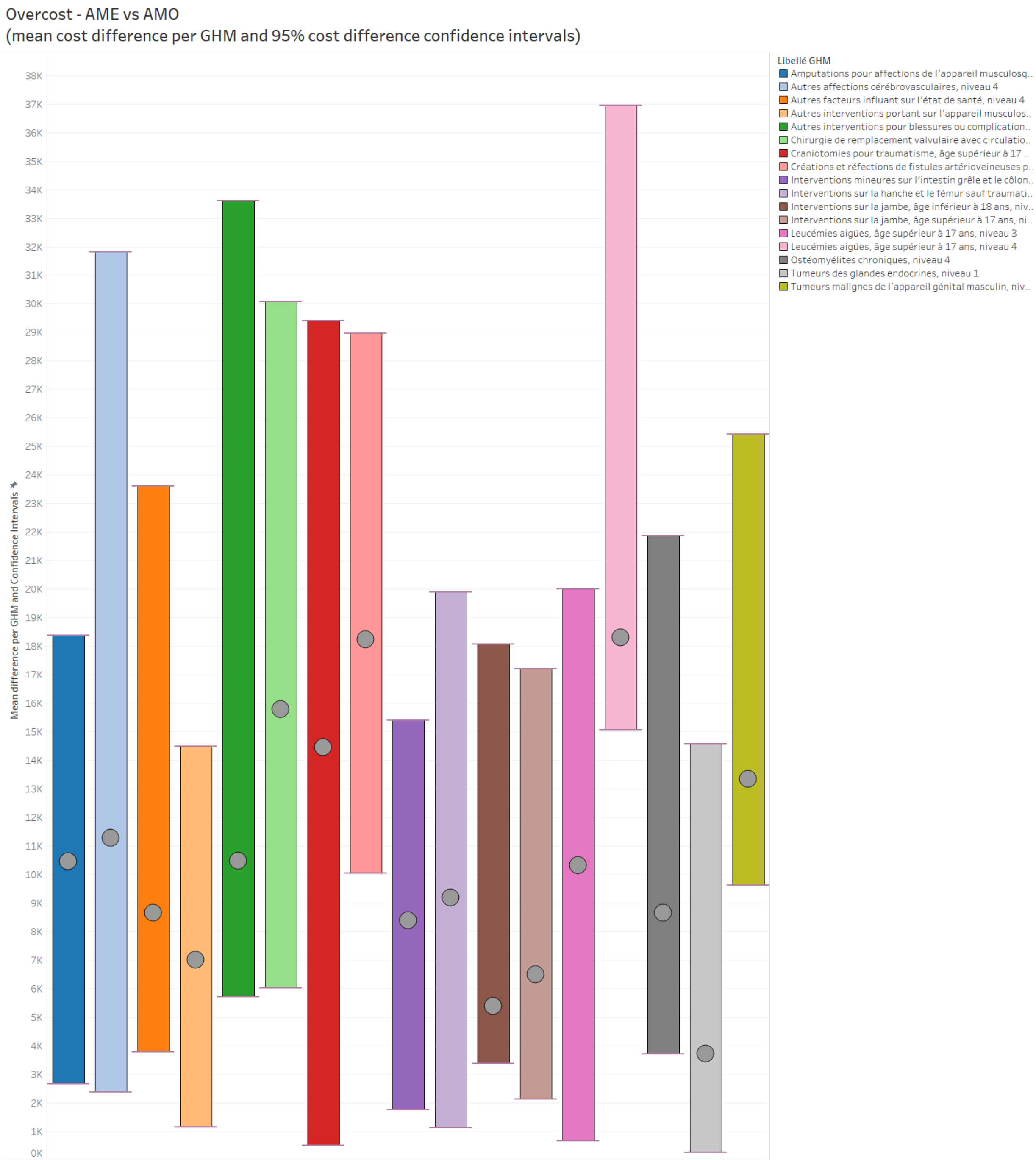


Figure 3.7: Stays Overcost - AME vs AMO (AYI)

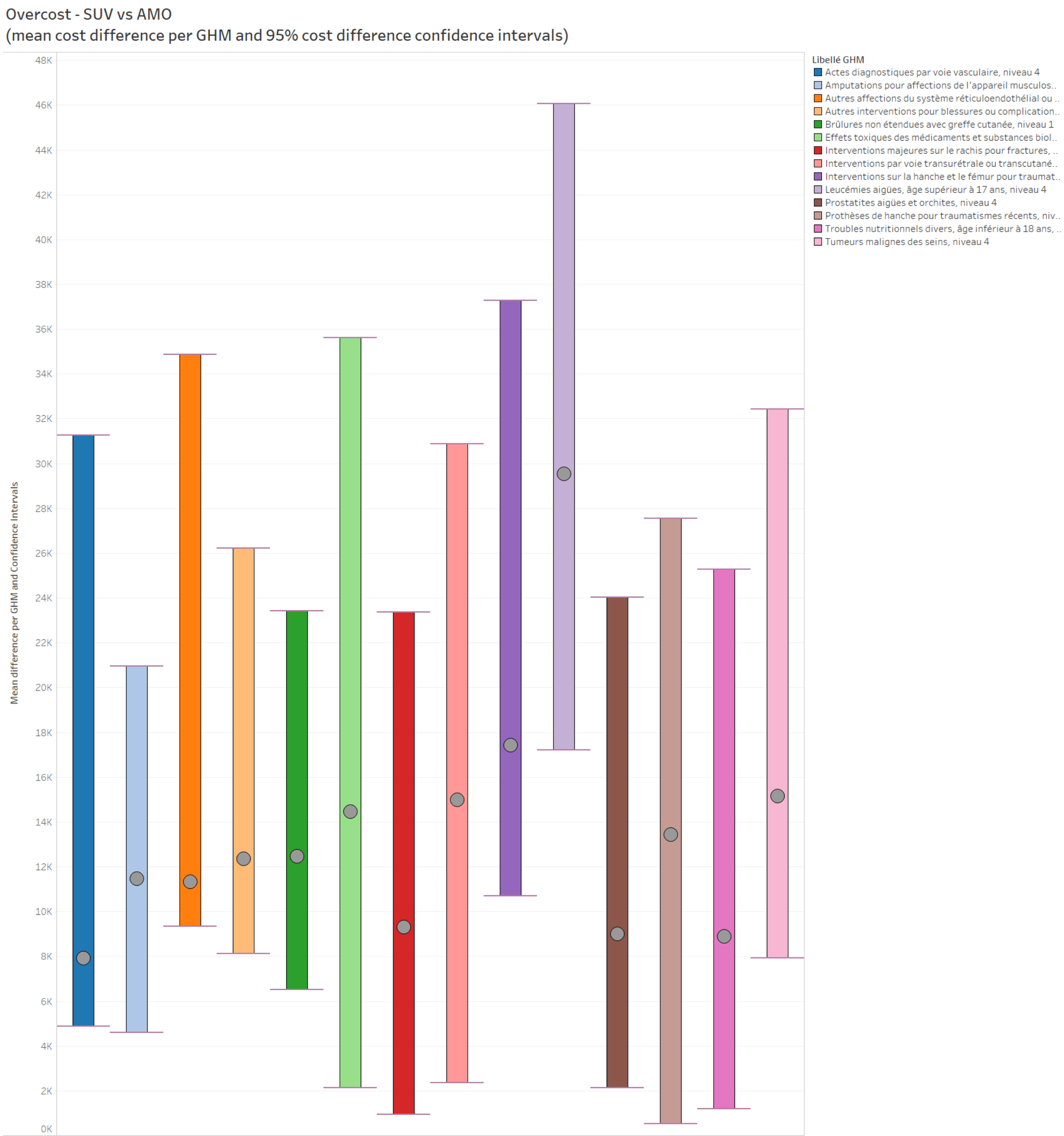


Figure 3.8: Stays Overcost - SUV vs AMO (AYI)

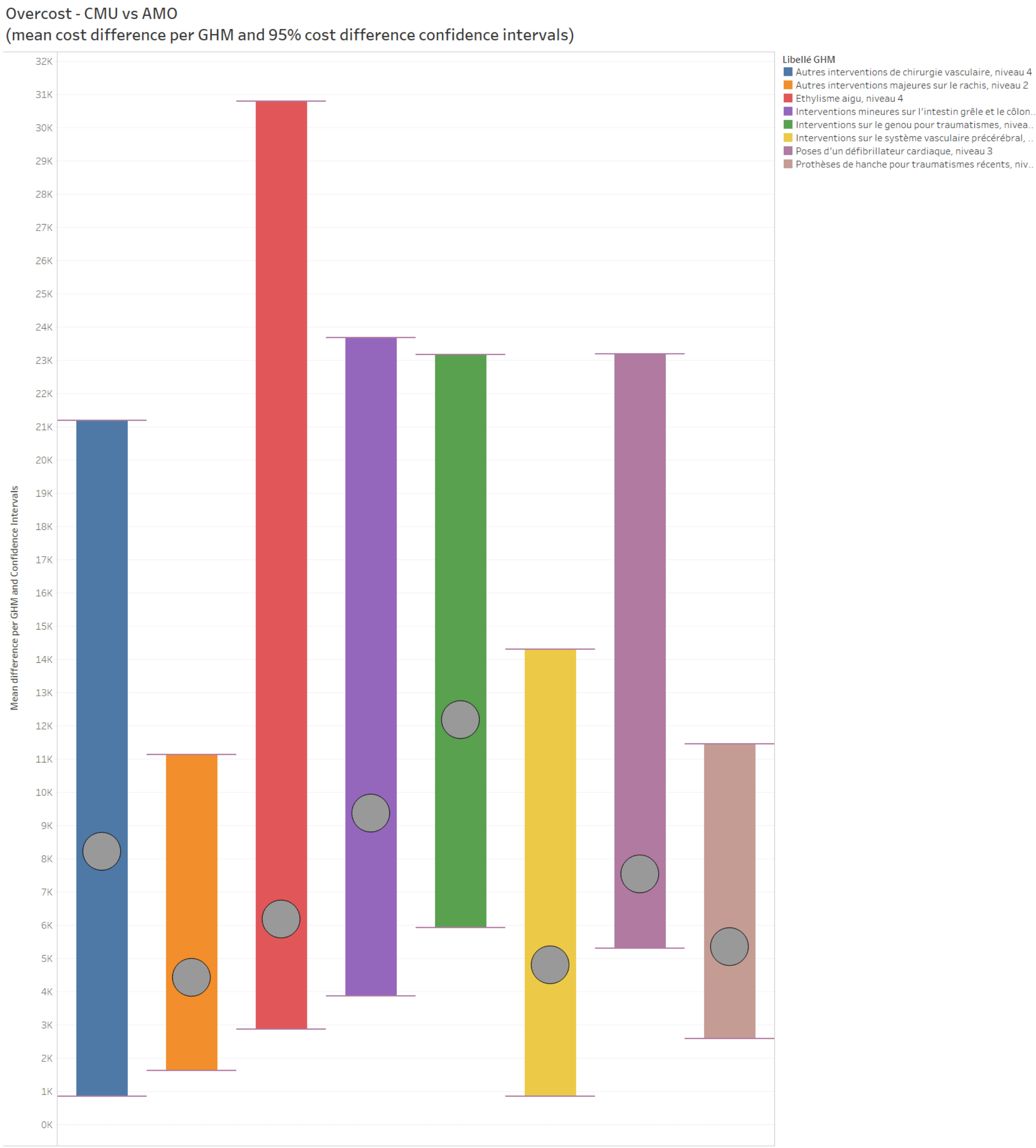


Figure 3.9: Stays Overcost - CMU-C vs AMO (AYI)

Chapter 4

Econometric modeling

In this chapter we go one step further in the quantification of the insights we can extract from the PMSI sample by specifying econometric models aimed at answering questions of interest. Our comparative analysis in term of precariousness premium and associated confidence intervals revealed a trend : AME, SUV, and CMU-C stays tend to be more expensive for more than 400 GHMs. Is this statement still holding true if we generalize our approach considering more data and controls ? In other words, is system membership decisive as a stay cost explaining factor ?

In a second time, we will investigate whether two specific public policies introduced during the 2011-2021 had a quantifiable impact the number of patients associated to each system. Indeed, it is assumed that the suppression of AME entry rights in 2013 as well as the introduction of a waiting period in 2020 for asylum seekers wishing to access to the general healthcare system generated an inflection in the incentives of AME and SUV beneficiaries leading to a modulation of systems patient volumes.

4.1 Cost explaining factors : is system membership decisive ?

After applying some data processing routines on our sample by :

1. Eliminating outliers using a statistical rule (stays having an abnormally high cost)
2. Generating useful control variables
3. Eliminating null values
4. Applying a Modified Park Test to select which underlying law corresponds to the cost distribution (found Poisson)

We fit the following General Linear Model:

$$\log(\text{cost}) = \beta_0 + \beta_d \mathbf{1}_{\text{Death}} + \beta_{\text{sex}} \mathbf{1}_{\text{Woman}} + \beta_s \mathbf{1}_{\text{GHMS}} + \beta_a \boldsymbol{age} + \beta_{asq} \boldsymbol{age}^2 + \sum_{k \in K} \beta_{cmd_k} \mathbf{1}_{cmd_k} + \sum_{s \in C} \beta_{CC_s} CC_s + \sum_{g \in T} \beta_{system} \mathbf{1}_{system_g} + \sum_{i \in R} \beta_{\text{region}_i} \mathbf{1}_{\text{region}_i} + \epsilon$$

Figure 4.1: GLM specification

We regresss the log cost on the following covariates :

1. death dummy indicating whether the stay ended up in an intra hospital death
2. sex dummy
3. age and age squared aimed at capturing the non linear effect of age on cost
4. GHMS : GHM severity dummy controlling whether the stay GHM is coded with a notion of severity (including all levels) or not
5. CMD dummy used to loosely control the typology of stay, CMD being general aggregates of GHM
6. Critical Care control dummy : leveraging critical care supplements, offers a gradation of criticality from 0 to 3
7. System membership dummy : the implicit dummy is AMO, allowwing for easier interpretation of coefficient
8. Regional control dummy

The regression results shown in the following figure comfort the idea that system membership has an impact on cost when we control for all the pre-cited covariates.All coefficients are statistically significant, and we even see a clear gradation on the coefficient giving SUV the highest dummy coefficient with respect to AMO (0.09), then AME (0.05) and CMU-C (0.007). In other words, being an SUV patient, ceteris paribus, implies an increase of 10% of the stay cost.

All other estimated coefficient are consistent with the previous analysis and intuition on the health care system. For example, we notice that the regions having the highest positive impact on stay costs are Mayotte and Guyane, generating respectively a 27% and 7.2% increase of stay costs all other things being equal.

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	6.8953	0.000	4.1e+04	0.000	6.895	6.896
sexe[T.2]	-0.0044	5.17e-05	-85.207	0.000	-0.005	-0.004
severity[T.Sévérité GHM]	1.0526	7.48e-05	1.41e+04	0.000	1.052	1.053
critical_care[T.CR1]	0.0711	0.000	508.276	0.000	0.071	0.071
critical_care[T.CR2]	0.3401	0.000	3196.871	0.000	0.340	0.340
critical_care[T.CR3]	0.5269	0.000	2927.056	0.000	0.527	0.527
death_status[T.Dead]	0.1220	0.000	825.874	0.000	0.122	0.122
raison[T.AME]	0.0576	6.87e-05	837.587	0.000	0.057	0.058
raison[T.CMU-C]	0.0074	6.33e-05	116.886	0.000	0.007	0.008
raison[T.SUV]	0.0987	0.000	920.395	0.000	0.098	0.099
cmd[T.1]	-0.4262	0.000	-2650.426	0.000	-0.427	-0.426
cmd[T.10]	-0.2132	0.000	-1111.461	0.000	-0.214	-0.213
cmd[T.11]	-0.3850	0.000	-2158.938	0.000	-0.385	-0.385
cmd[T.12]	-0.4135	0.000	-1333.438	0.000	-0.414	-0.413
cmd[T.13]	-0.2707	0.000	-978.937	0.000	-0.271	-0.270
cmd[T.14]	0.7605	0.000	4892.234	0.000	0.760	0.761
cmd[T.15]	0.8114	0.000	2158.133	0.000	0.811	0.812
cmd[T.16]	-0.1387	0.000	-697.259	0.000	-0.139	-0.138
cmd[T.17]	-0.0678	0.000	-183.265	0.000	-0.069	-0.067
cmd[T.18]	-0.3724	0.000	-1648.957	0.000	-0.373	-0.372
cmd[T.19]	-0.3371	0.000	-1689.401	0.000	-0.338	-0.337
cmd[T.2]	-0.4273	0.000	-1296.150	0.000	-0.428	-0.427
cmd[T.20]	-1.2381	0.000	-5549.379	0.000	-1.239	-1.238
cmd[T.21]	-0.4936	0.000	-2230.748	0.000	-0.494	-0.493
cmd[T.22]	0.0966	0.000	193.434	0.000	0.096	0.098
cmd[T.25]	1.0157	0.000	2505.715	0.000	1.015	1.017
cmd[T.26]	-0.0205	0.001	-32.765	0.000	-0.022	-0.019
cmd[T.27]	0.1951	0.005	41.272	0.000	0.186	0.204
cmd[T.28]	-0.4433	0.000	-894.056	0.000	-0.444	-0.442
cmd[T.3]	-0.4235	0.000	-2038.416	0.000	-0.424	-0.423
cmd[T.4]	-0.2826	0.000	-1838.588	0.000	-0.283	-0.282
cmd[T.5]	-0.3267	0.000	-2035.930	0.000	-0.327	-0.326
cmd[T.6]	-0.2581	0.000	-1645.676	0.000	-0.258	-0.258
cmd[T.7]	-0.0806	0.000	-444.797	0.000	-0.081	-0.080
cmd[T.8]	-0.1536	0.000	-964.145	0.000	-0.154	-0.153
cmd[T.9]	-0.4904	0.000	-2603.415	0.000	-0.491	-0.490
region[T.AUVERGNE-RHÔNE-ALPES]	-0.0482	9.01e-05	-535.380	0.000	-0.048	-0.048
region[T.BOURGOGNE-FRANCHE-COMTÉ]	-0.0597	0.000	-426.150	0.000	-0.060	-0.059
region[T.BRETAGNE]	-0.0392	0.000	-302.363	0.000	-0.039	-0.039
region[T.CENTRE-VAL DE LOIRE]	-0.0437	0.000	-324.712	0.000	-0.044	-0.043
region[T.CORSE]	-0.0627	0.000	-148.901	0.000	-0.064	-0.062
region[T.GRAND EST]	-0.0356	0.000	-352.225	0.000	-0.036	-0.035
region[T.GUADELOUPE]	-0.0471	0.000	-255.203	0.000	-0.047	-0.047
region[T.GUYANE]	0.0704	0.000	693.912	0.000	0.070	0.071
region[T.HAUTS-DE-FRANCE]	-0.0639	8.4e-05	-761.336	0.000	-0.064	-0.064
region[T.LA RÉUNION]	-0.0457	0.000	-220.553	0.000	-0.046	-0.045
region[T.MARTINIQUE]	0.0116	0.000	43.790	0.000	0.011	0.012
region[T.MAYOTTE]	0.2442	0.000	751.221	0.000	0.244	0.245
region[T.NORMANDIE]	-0.0651	0.000	-471.325	0.000	-0.065	-0.065
region[T.NOUVELLE-AQUITAINE]	-0.0721	0.000	-720.358	0.000	-0.072	-0.072
region[T.OCCITANIE]	-0.0558	0.000	-504.601	0.000	-0.056	-0.056
region[T.PAYS DE LA LOIRE]	-0.0527	0.000	-448.545	0.000	-0.053	-0.052
region[T.PROVENCE-ALPES-CÔTE D'AZUR]	-0.0549	9.54e-05	-575.310	0.000	-0.055	-0.055
age	0.0050	3.31e-06	1495.480	0.000	0.005	0.005
np.power(age, 2)	1.736e-05	3.57e-08	486.594	0.000	1.73e-05	1.74e-05

Figure 4.2: GLM results

4.2 Patient volume per system: does public policy have an impact ?

In order to get a quantitative answer to this question, we will leverage the Difference-in-Difference framework. Due to the modest size of yearly volumes available (10 years per system), we put special attention into being within the assumptions of the model. To do so, we carefully tried to find trends allowing for such regression. We will distinguish global DID regressions including all regions and specifically regional volume trends that were aligned with the model assumptions.

We will assume an underlying General Linear Model with the following specification :

$$log(volume) = \beta_0 + \beta_1 \mathbb{1}_{treat} + \beta_2 \mathbb{1}_{post} + \lambda \mathbb{1}_{treat} * \mathbb{1}_{post} + \epsilon$$

Figure 4.3: DID specification

1. Treat dummy corresponds to whether the system is directly impacted by the public policy
2. Post: time dummy corresponding to the introduction and effectiveness of the public policy

λ is our coefficient of interest here as it capture the causal effect of the policy on the targeted group. We will divide this section according to the analysis of the 2013 and 2020 public policies impact on patient volumes per system.

4.2.1 2013 : removal of AME's entry rights

yearly

The most critical DID regression assumption is the parrallel trend assumption. Analyzing the yearly patients volume per system over time for the Guadeloupe, we observe a pre-treatment parrallel trend for AME and CMU-C at a year before the removal of AME's entry rights in 2013.

Thus, we perform a DID regression in order to estimate the causal effect of this policy on the AME contingent as we can assume that due to its population characteristics, it is the one being directly impacted by this measure. AME will consequently act as our treatment group, CMU-C being the control. Furthermore, we suppose that the public policy dynamic effect on patient volumes vanishes after 3 years.

We have statistically significant results, pointing us to a multiplication by a factor of 2.5 of the AME volume in Guadeloupe after the introduction of the public policy.

Figure 4.4: Yearly patient volume per system - GUADELOUPE

Generalized Linear Model Regression Results

Dep. Variable:	volume	**No. Observations:**	10
Model:	GLM	**Df Residuals:**	6
Model Family:	Poisson	**Df Model:**	3
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-266.07
Date:	Wed, 29 Jun 2022	**Deviance:**	456.71
Time:	13:11:55	**Pearson chi2:**	386.
No. Iterations:	4		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	5.9890	0.050	119.629	0.000	5.891	6.087
treat	-0.3330	0.077	-4.298	0.000	-0.485	-0.181
post	-0.4755	0.059	-8.022	0.000	-0.592	-0.359
treat:post	0.9266	0.087	10.651	0.000	0.756	1.097

Figure 4.5: DID regression results

monthly

quaterly

Figure 4.6: Monthly patient volume per system - Global

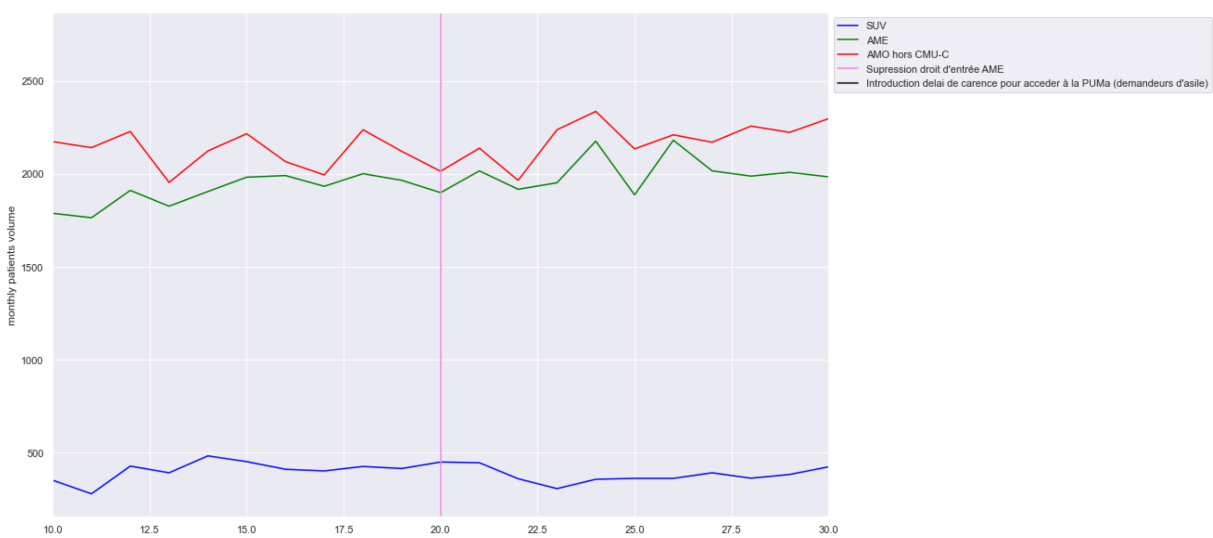


Figure 4.7: Monthly patient volume per system - Global, circa PP

Generalized Linear Model Regression Results

Dep. Variable:	volume	**No. Observations:**	52
Model:	GLM	**Df Residuals:**	48
Model Family:	Poisson	**Df Model:**	3
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-786.49
Date:	Thu, 04 Aug 2022	**Deviance:**	1084.3
Time:	13:20:47	**Pearson chi2:**	1.01e+03
No. Iterations:	4		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	7.6444	0.005	1562.465	0.000	7.635	7.654
treat	-0.1957	0.007	-26.871	0.000	-0.210	-0.181
post	0.0229	0.010	2.273	0.023	0.003	0.043
treat:post	0.1165	0.015	7.935	0.000	0.088	0.145

Figure 4.8: DID regression results

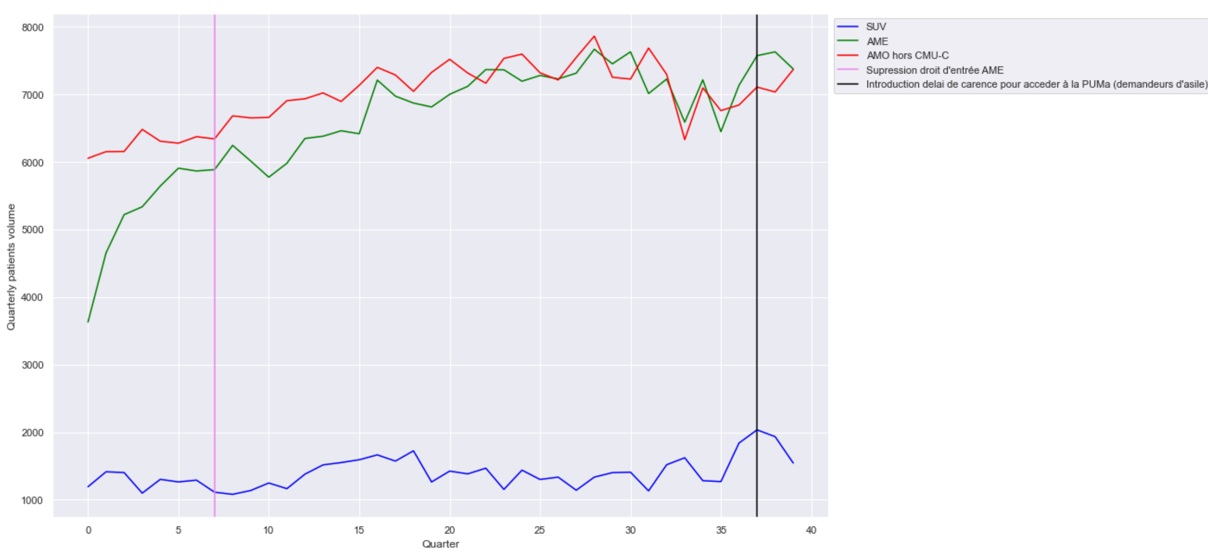


Figure 4.9: Quarterly patient volume per system - Global

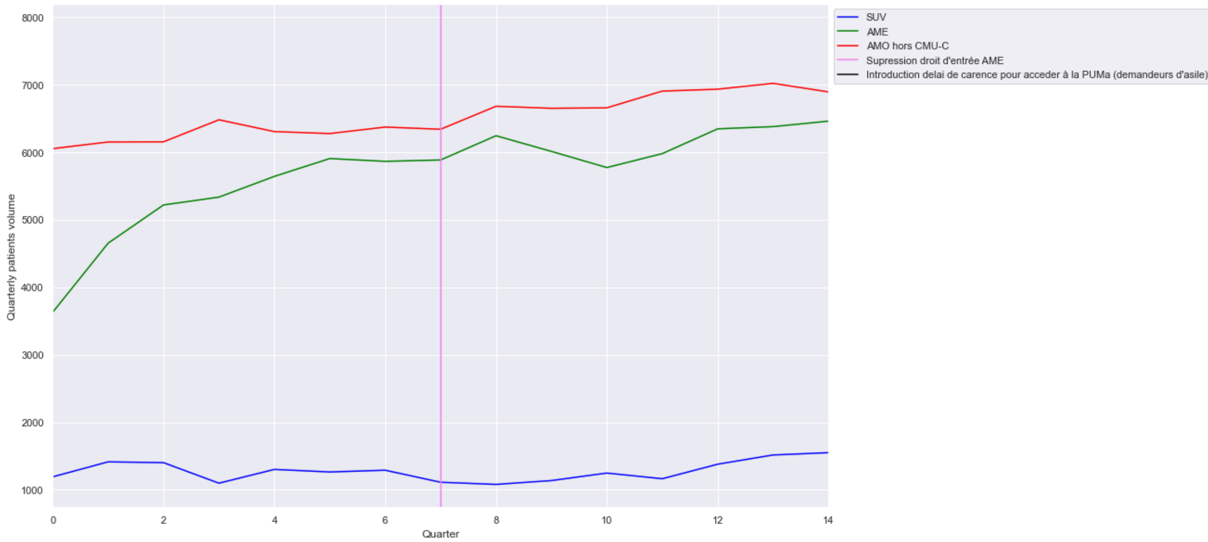


Figure 4.10: Monthly patient volume per system - Global, circa PP

Generalized Linear Model Regression Results

Dep. Variable:	volume	**No. Observations:**	22
Model:	GLM	**Df Residuals:**	18
Model Family:	Poisson	**Df Model:**	3
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-249.63
Date:	Thu, 04 Aug 2022	**Deviance:**	267.28
Time:	13:14:12	**Pearson chi2:**	263.
No. Iterations:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	8.7467	0.005	1699.151	0.000	8.737	8.757
treat	-0.1457	0.008	-19.278	0.000	-0.161	-0.131
post	0.0552	0.008	7.334	0.000	0.040	0.070
treat:post	0.0399	0.011	3.628	0.000	0.018	0.061

Figure 4.11: DID regression results

4.2.2 2020 : introduction of a waiting period for asylum seekers for accessing the general healthcare system

All regions included

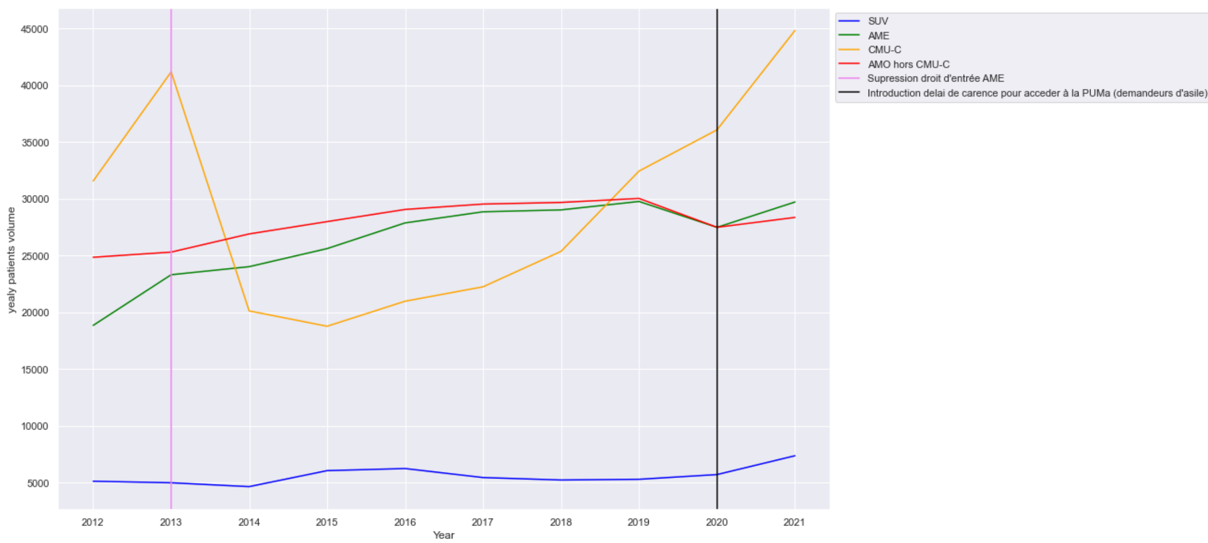


Figure 4.12: Yearly patient volume per system - All regions included

We observe a pre-treatment parrallel trend for AME and AMO at least two years before the introduction of a waiting period for asylum seekers willing to access PUMa.

With the same framework as before we perform a DID regression considering AME as our treatment group, the base system AMO being the control.

We have statistically significant results for λ, revealing a global increase of 10% of AME patients after the 2020 public policy controlling the access of asylum seekers to the heath care system.

Generalized Linear Model Regression Results

Dep. Variable:	volume	**No. Observations:**	20
Model:	GLM	**Df Residuals:**	16
Model Family:	Poisson	**Df Model:**	3
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2652.6
Date:	Wed, 29 Jun 2022	**Deviance:**	5064.3
Time:	12:08:47	**Pearson chi2:**	4.89e+03
No. Iterations:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	10.2367	0.002	4836.871	0.000	10.233	10.241
treat	-0.0746	0.003	-24.451	0.000	-0.081	-0.069
post	0.0002	0.005	0.033	0.974	-0.009	0.009
treat:post	0.0985	0.007	14.734	0.000	0.085	0.112

Figure 4.13: DID regression results

Guyane

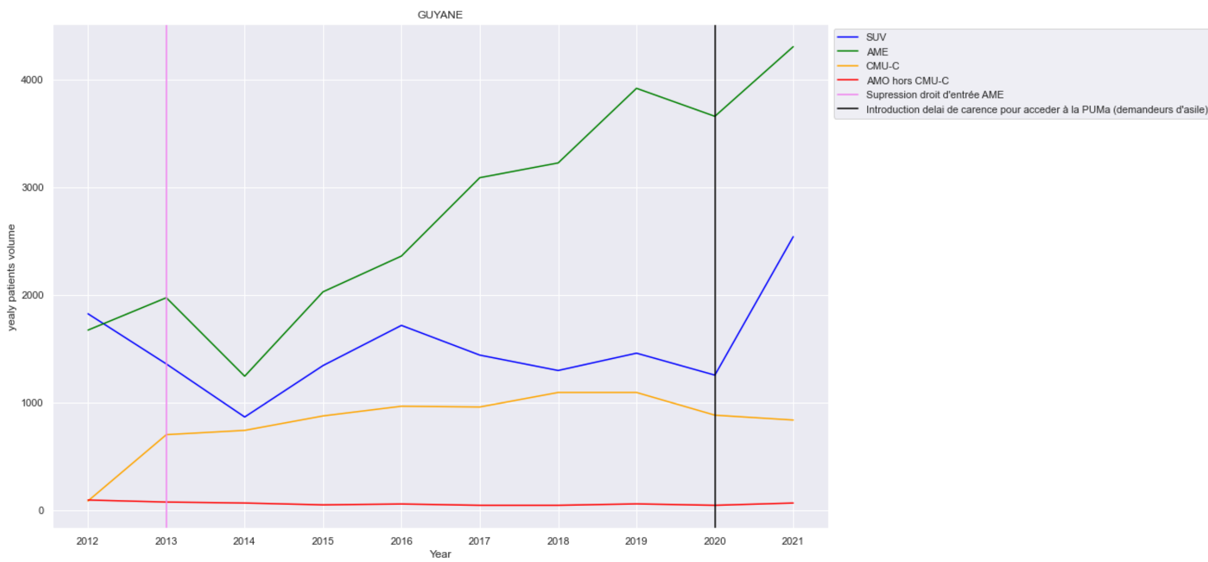


Figure 4.14: Yearly patient volume per system - Guyane

We observe a pre-treatment parrallel trend for AME and CMU-C contingents in Guyane at least two years before the introduction of a waiting period for asylum seekers willing to access PUMa.

With the same framework as before we perform a DID regression considering AME as our treatment group, the base system CMU-C being the control.

We have statistically significant results for λ, revealing an increase 53% of AME patients in Guyane after the 2020 public policy controlling the access of asylum seekers to the heath care system.

Generalized Linear Model Regression Results

Dep. Variable:	volume	**No. Observations:**	20
Model:	GLM	**Df Residuals:**	16
Model Family:	Poisson	**Df Model:**	3
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1935.1
Date:	Wed, 29 Jun 2022	**Deviance:**	3689.4
Time:	13:15:26	**Pearson chi2:**	3.29e+03
No. Iterations:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	6.6993	0.012	539.911	0.000	6.675	6.724
treat	1.0990	0.014	76.705	0.000	1.071	1.127
post	0.0547	0.027	2.014	0.044	0.001	0.108
treat:post	0.4359	0.030	14.419	0.000	0.377	0.495

Figure 4.15: DID regression results

monthly

Figure 4.16: Monthly patient volume per system - Global

Figure 4.17: Monthly patient volume per system - Global, circa PP

Generalized Linear Model Regression Results

Dep. Variable:	volume	**No. Observations:**	32
Model:	GLM	**Df Residuals:**	28
Model Family:	Poisson	**Df Model:**	3
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-247.34
Date:	Thu, 04 Aug 2022	**Deviance:**	211.57
Time:	13:16:14	**Pearson chi2:**	209.
No. Iterations:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	7.7237	0.008	971.743	0.000	7.708	7.739
treat	-1.6330	0.020	-83.055	0.000	-1.672	-1.594
post	0.0320	0.011	3.039	0.002	0.011	0.053
treat:post	0.3124	0.025	12.625	0.000	0.264	0.361

Figure 4.18: DID regression results

quaterly

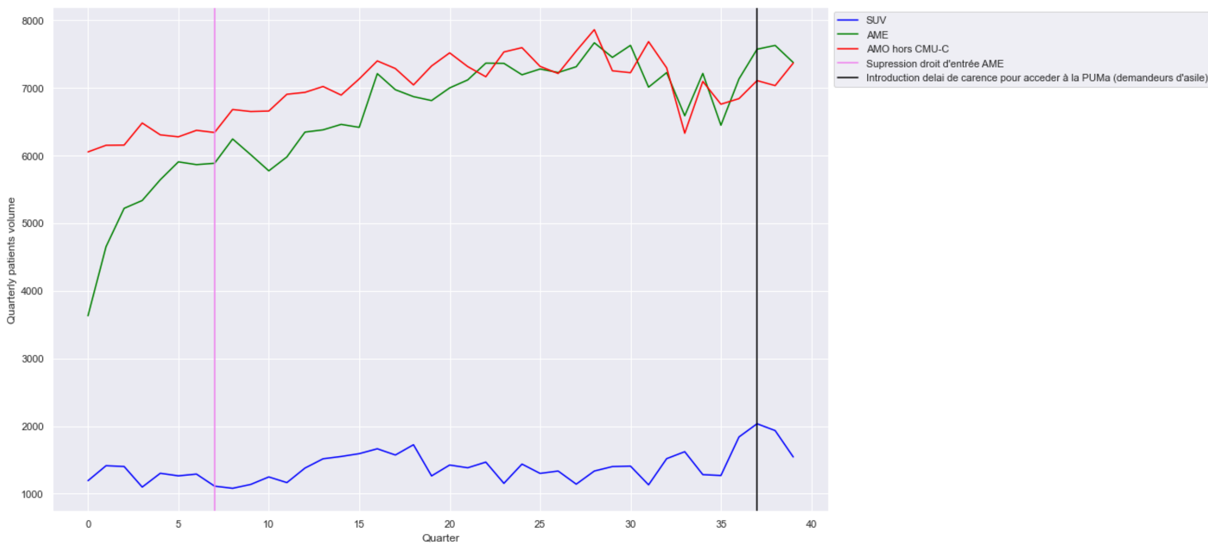


Figure 4.19: Quarterly patient volume per system - Global

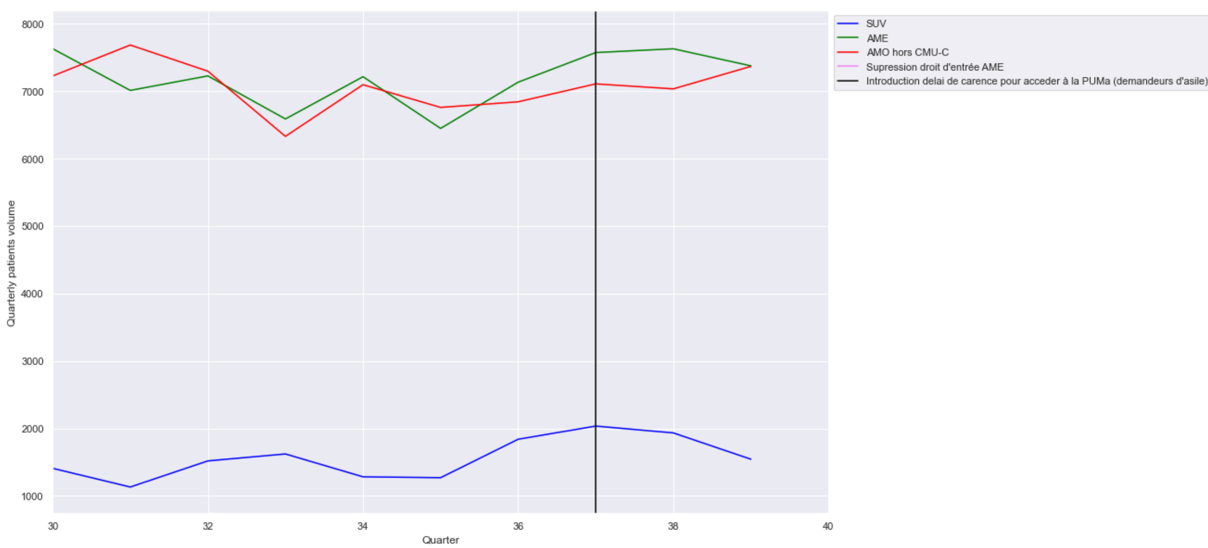


Figure 4.20: Monthly patient volume per system - Global, circa PP

Generalized Linear Model Regression Results

Dep. Variable:	volume	**No. Observations:**	8
Model:	GLM	**Df Residuals:**	4
Model Family:	Poisson	**Df Model:**	3
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-81.897
Date:	Thu, 04 Aug 2022	**Deviance:**	83.583
Time:	13:09:50	**Pearson chi2:**	81.7
No. Iterations:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	8.8307	0.012	730.389	0.000	8.807	8.854
treat	-1.3132	0.026	-50.004	0.000	-1.365	-1.262
post	0.0468	0.014	3.371	0.001	0.020	0.074
treat:post	-0.0481	0.030	-1.586	0.113	-0.107	0.011

Figure 4.21: DID regression results

Chapter 5

Conclusion

Globally, SUV and AME are detached from CMU-C and AMO due to a hand-full of stylized facts. They distinguish themselves through the predominance of younger patients, mainly present for obstetrics care. They tend to be localized in the capital city and in the french overseas regions. Their stays are correlated with a higher cost in comparison with the basic system as well as a higher severity, in particular from the point of view of the duration of hospitalization in intensive care.

Econometric modelling demonstrates that system membership is a particularly important cost explaining factor and exhibits a clear gradation of this impact : the more the system is targeted to a precarious population, the higher the impact on cost, up to 10% of the overall stay cost all other things equal.

Finally, the direct impact of public policy on the patient contingents of these systems is hard to capture rigorously on french healthcare system as a whole. The 2013 removal of AME's entry rights had generated an important increase of the Guadeloupe region AME contingent relative to the CMU-C control contingent. However, the 2020 introduction of a waiting period for asylum seekers for accessing the general healthcare system had an impact that we were able to quantify on the whole french territory. This public policy was associated with a 10% increase of AME contigent when we consider the AMO system as control.

Further work will be put forward in order to precisely account for the porosity between systems, especially between AME and SUV. Preliminary analyzes already lead us to the observation of crossed paths, particularly in the overseas regions. Theses investigations will grant us the ability to further nuance the impact of public policies by pinning down the potential changes in these hospital pathways as well as refining the effective differences between this two specifically targeted health care access systems.

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