



# Better planning through Design

## Forecasting Enrollment in Clinical Trials When Site-Level Accrual Rates Vary with Time

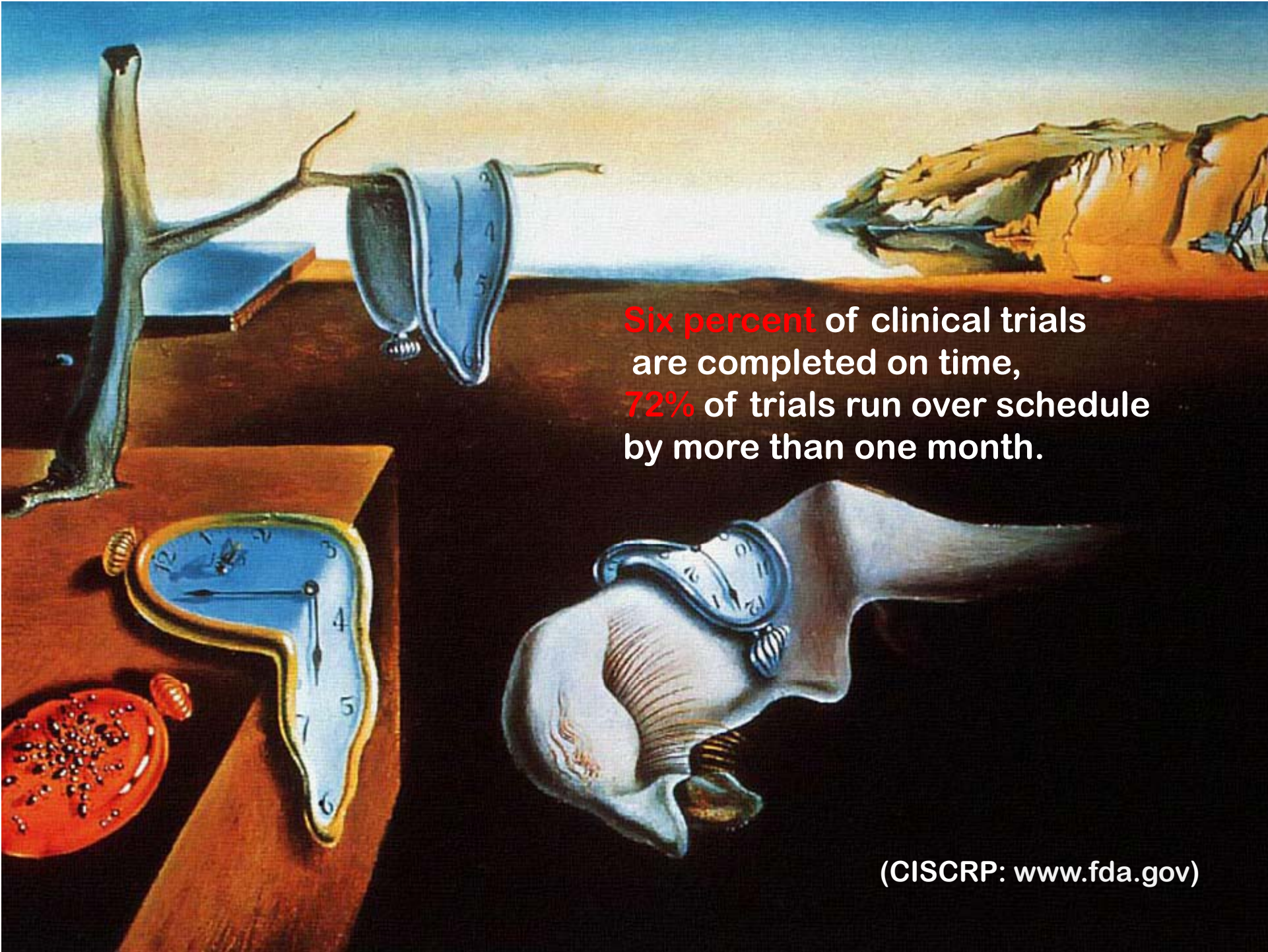
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**Nitin Patel, Pralay Senchaudhuri, Suresh Ankolekar**  
Presented by **Yannis Jemai**

# Outline

- Motivation and background
- Poisson-Gamma: a reasonable model to forecast enrolment
- Improving predictions through stratification
- Ignoring the first inter-arrival time
- Time-variant enrolment rates
- Conclusions

# **Motivation and Background**



**Six percent** of clinical trials are completed on time, **72%** of trials run over schedule by more than one month.

(CISCRP: [www.fda.gov](http://www.fda.gov))

## Other facts and figures

- Eighty percent of total trials are delayed at least one month because of unfulfilled enrollment. (Lamberti, "State of Clinical Trials Industry", 292)
- Out of all of the research sites in the United States, less than a 1/3 contain 70% of the valuable subjects. Therefore 70% of the research sites under-perform, and somewhere between 15%-20% never even enroll a single patient. (Pierre, "Recruitment and Retention". 2006)
- Fifty percent of clinical research sites enroll one or no patients in their studies. (Pierre, "Recruitment and Retention". 2006)

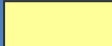
# Why model enrolment?

- Significant resources and strategic planning are contingent upon the timing of interim and final data analyses
- Modeling recruitment and event accrual based on current accumulated data allows early and accurate predictions of interim analysis times and study termination
- Statistical modeling also provides confidence levels for predictions

# Large pharma enrolment data for trials with more than 200 subjects

Seq#	Therapeutic Area	Study Phase	# Sites	# Subjects	# Countries
1	CVID&MET	Phase 3	118	993	30
2	INFL&IM	Phase 2	36	249	1
3			62	365	9
4			71	242	8
5	Neuroscience	Phase 2	56	227	10
6			61	342	11
7			49	237	11
8			32	314	2
9			27	204	1
10		Phase 3	25	474	1
11			43	485	10
12			21	638	1
13			65	608	5
14			36	387	1
15			57	713	1
16			46	412	1
17			44	245	1

Seq#	Therapeutic Area	Study Phase	# Sites	# Subjects	# Countries
18	Vaccines	Phase 3	38	667	1
19			56	606	1
20			9	286	1
21			38	613	1
22			15	500	1
23			4	354	1
24			9	269	3
25			9	355	1
26			79	1712	1
27			23	449	1
28			11	603	1
29			9	606	1
30			35	619	1
31			25	1241	1
32			61	1053	1
33			34	1116	1
34			2	270	1
35			39	1165	4
36			21	718	1
37	WH&BR	Phase 3	21	495	3
38			34	458	1
39			62	533	2

Trials conducted in more than 5 countries highlighted in yellow 

**Poisson-Gamma: a reasonable model to  
forecast enrolment**



# Predicting if a trial will complete on time

- Consider a multicenter trial that starts at time zero and is planned to enrol  $n$  subjects by time  $T$
- Suppose that at time  $t_0 < T$ ,  $K$  centers have been opened at times  $a_1, a_2, \dots, a_K (\leq t_0)$ .
- Let  $n_{0i}$  be the number of subjects accrued in center  $i$ ,  $i=1, 2, \dots, K$  at time  $t_0$
- We would like to estimate the probability of completing the trial on time (i.e., by time  $T$ ).

# A Bayesian approach

- Based on Poisson-Gamma model (Anisimov & Fedorov, 2007)
- Assume that accruals at center  $i$  follow a Poisson process with rate  $\mu_i$ .
- We also assume that  $\mu_i$  has a Gamma prior with parameters  $(\alpha_i, \beta_i)$ , and accruals at centers are mutually independent.
- It is well-known that the posterior distribution of  $\mu_i$  (computed at  $t_0$ ) is a Gamma distribution with parameters  $(n_{0i} + \alpha_i, t_0 - a_i + \beta_i)$ .

# Predictive probability of future accruals

- The predictive probability of  $n_{1i}$  – the number of accruals at center  $i$  during  $(t_0, T)$  is Negative Binomial with parameters

$$(n_{0i} + \alpha_i, (t_0 - a_i + \beta_i) / (T - a_i + \beta_i))$$

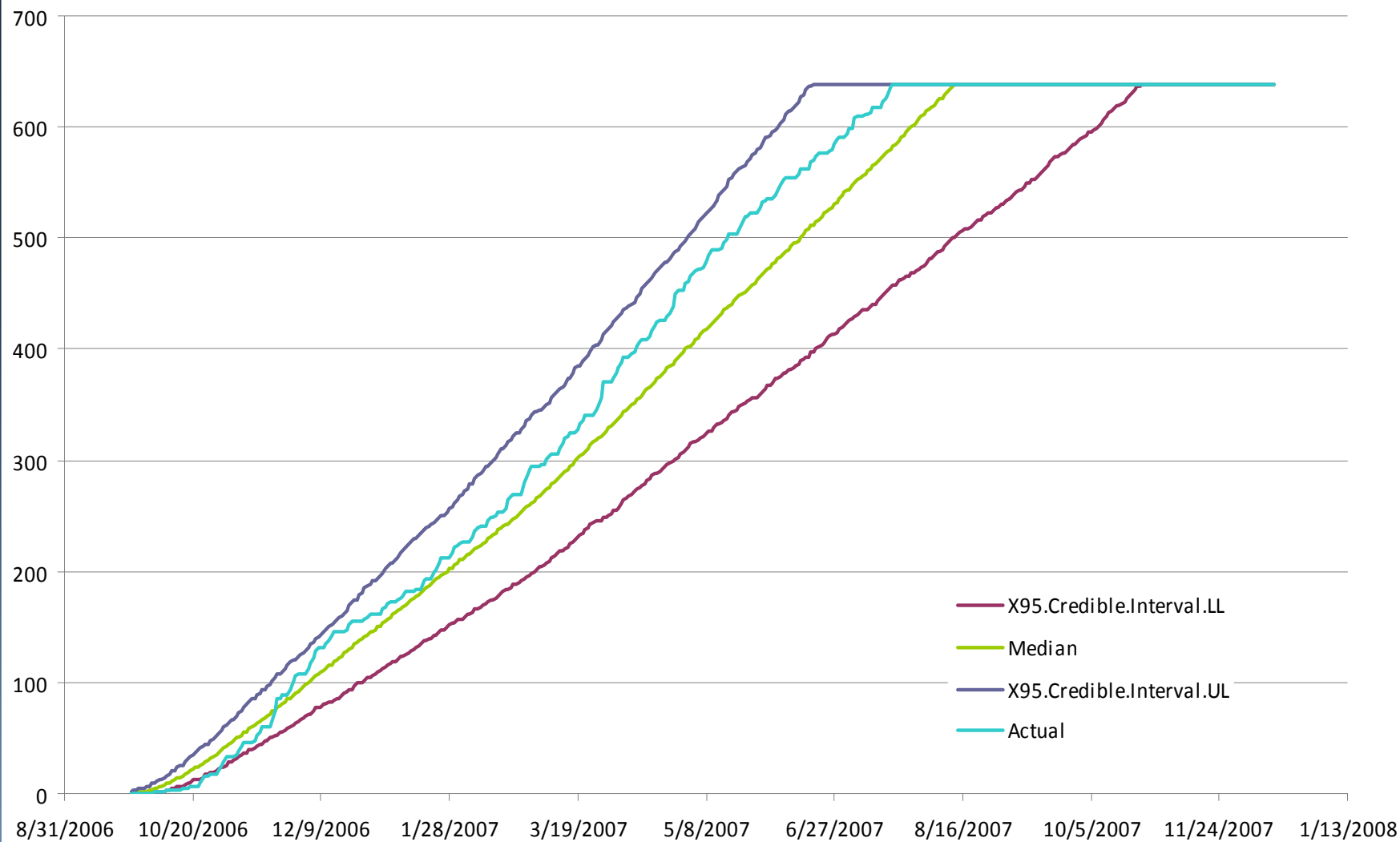
- Computing the probability of accruing  $n$  subjects by time  $T$  involves figuring out the convolution of  $K$  negative binomials
- In general no closed solution. It's easiest to obtain a Monte Carlo estimate through simulation.

# Simulation assumptions

- In the simplest version of the model, we assume that  $\mu_i$  has a Gamma prior with parameters  $(\alpha, \beta)$
- We simulate 500 runs to obtain median and credible intervals for end time  $T$
- To make comparisons between models fair, we take the truth as our prior, i.e. get  $\alpha$  and  $\beta$  from the data
- Calculate mean and standard deviation of the enrolment rate from data and use to obtain  $\alpha$  and  $\beta$
- Site Initiation Visit (SIV) times are assumed to be known and not predicted

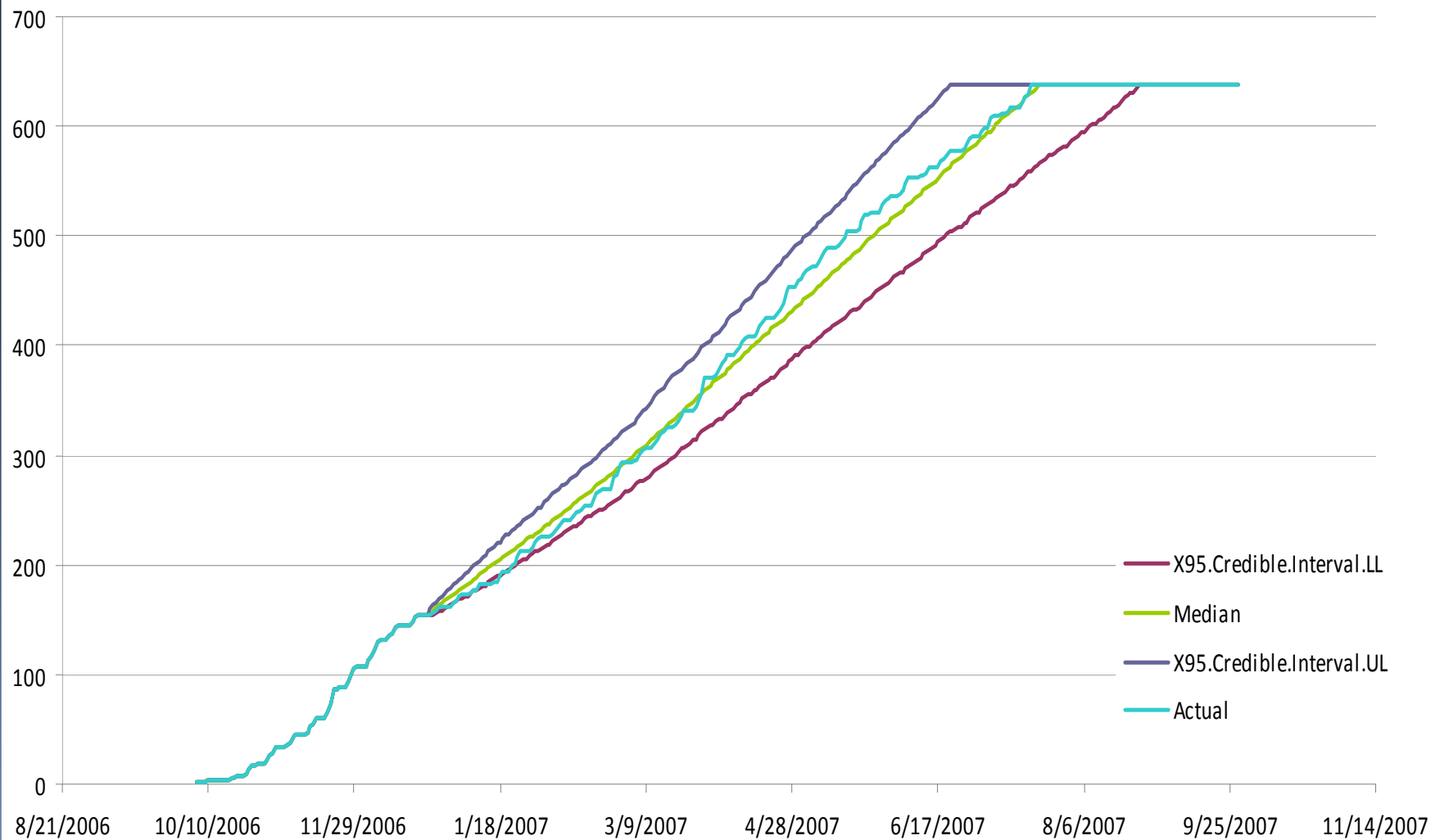
# Prediction at time $t_0 = 0$ months

Trial1 : Unstratified Enrollment Prediction at t=0



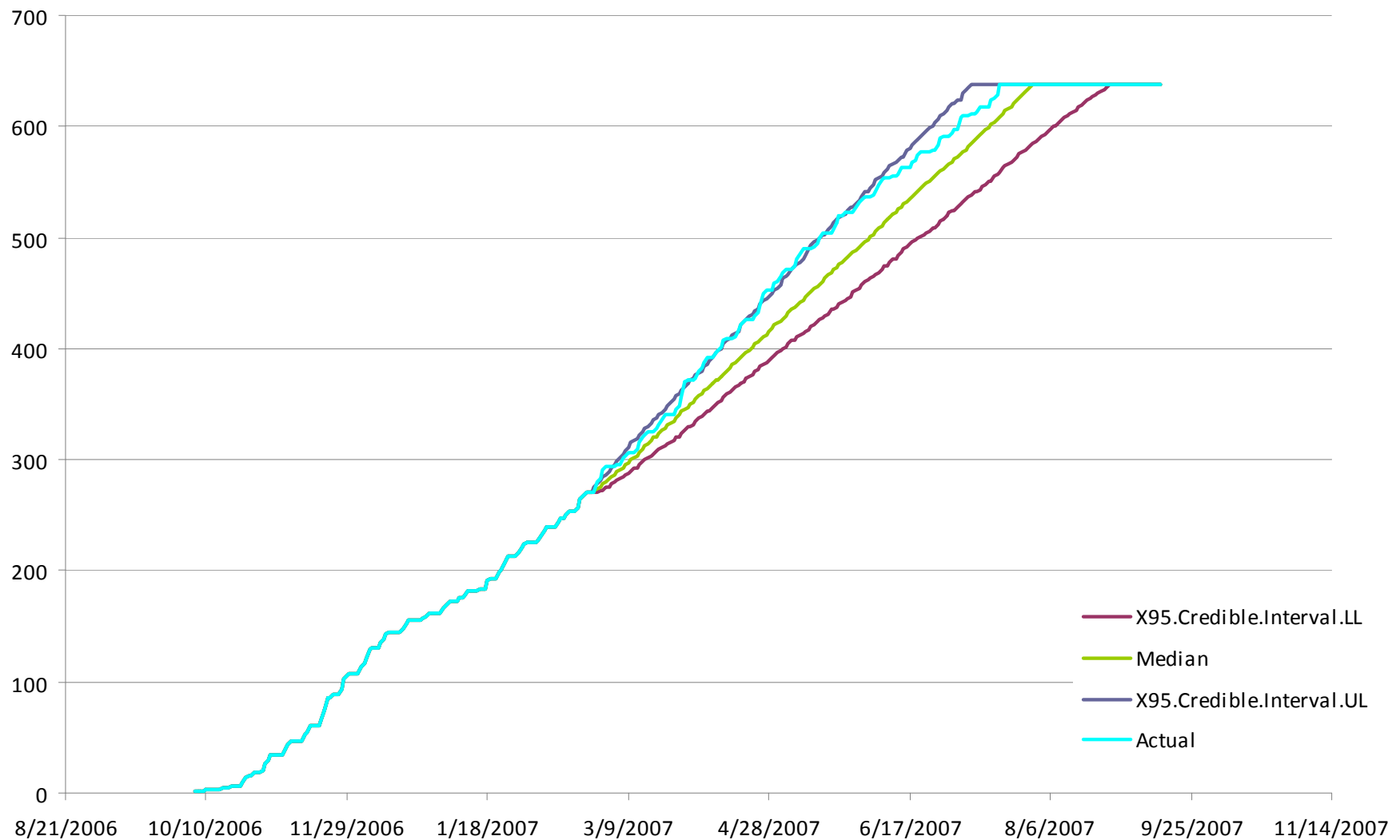
# Prediction at time $t_0 = 3$ months

Trial1 : Unstratified Enrollment Prediction at t=3



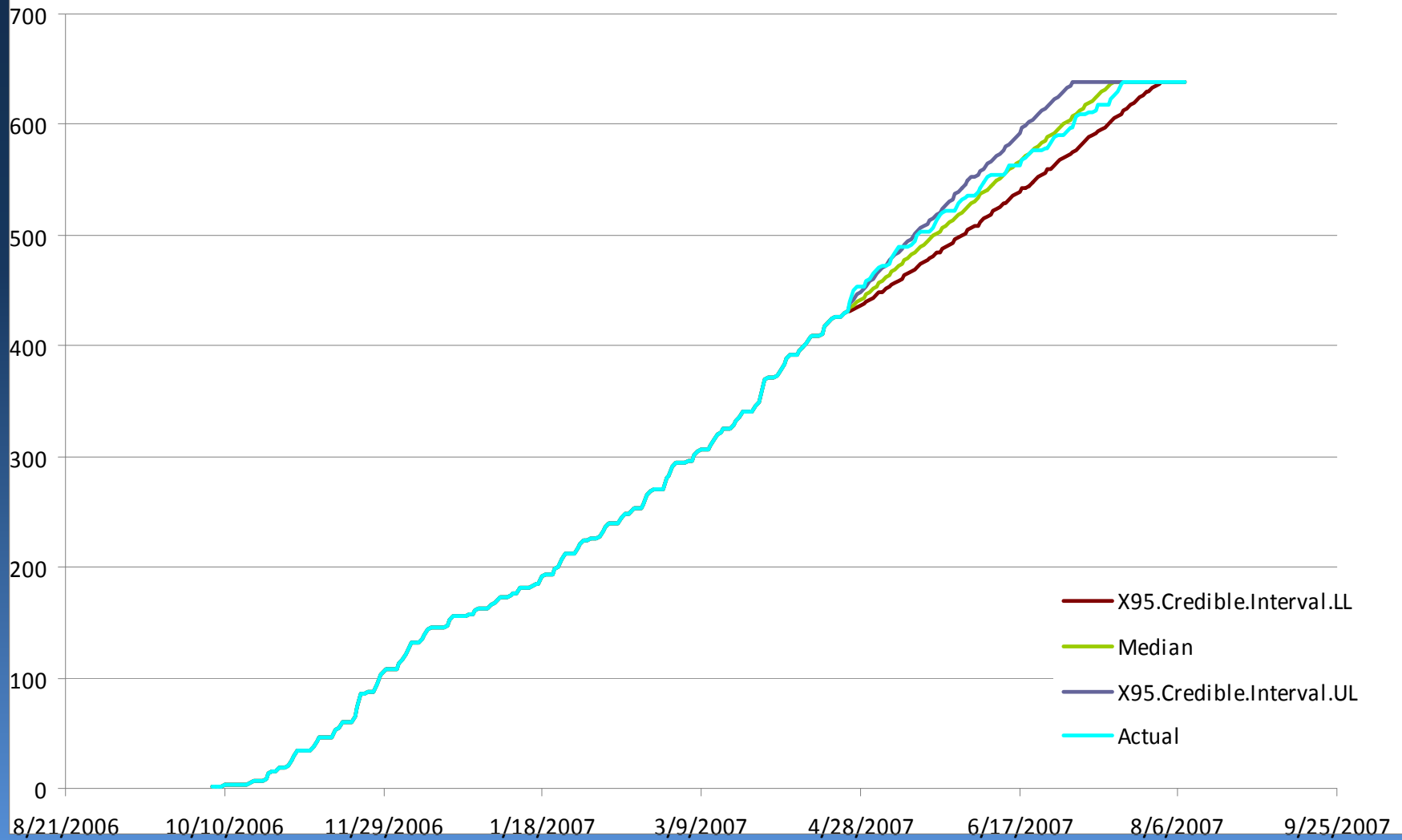
# Prediction at time $t_0 = 5$ months

Trial1 : Unstratified Enrollment Prediction at t=5



# Prediction at time $t_0 = 7$ months

Trial1 : Unstratified Enrollment Prediction at t=7





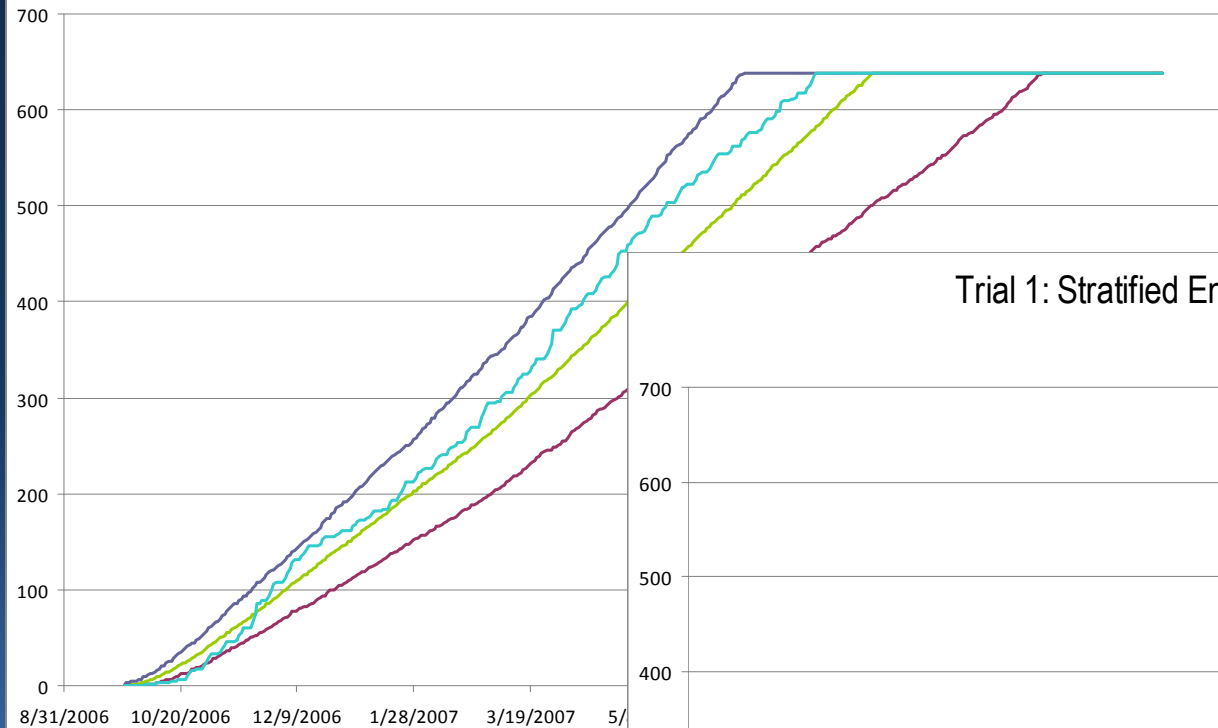
**Improving predictions through  
stratification**

# Stratifying sites

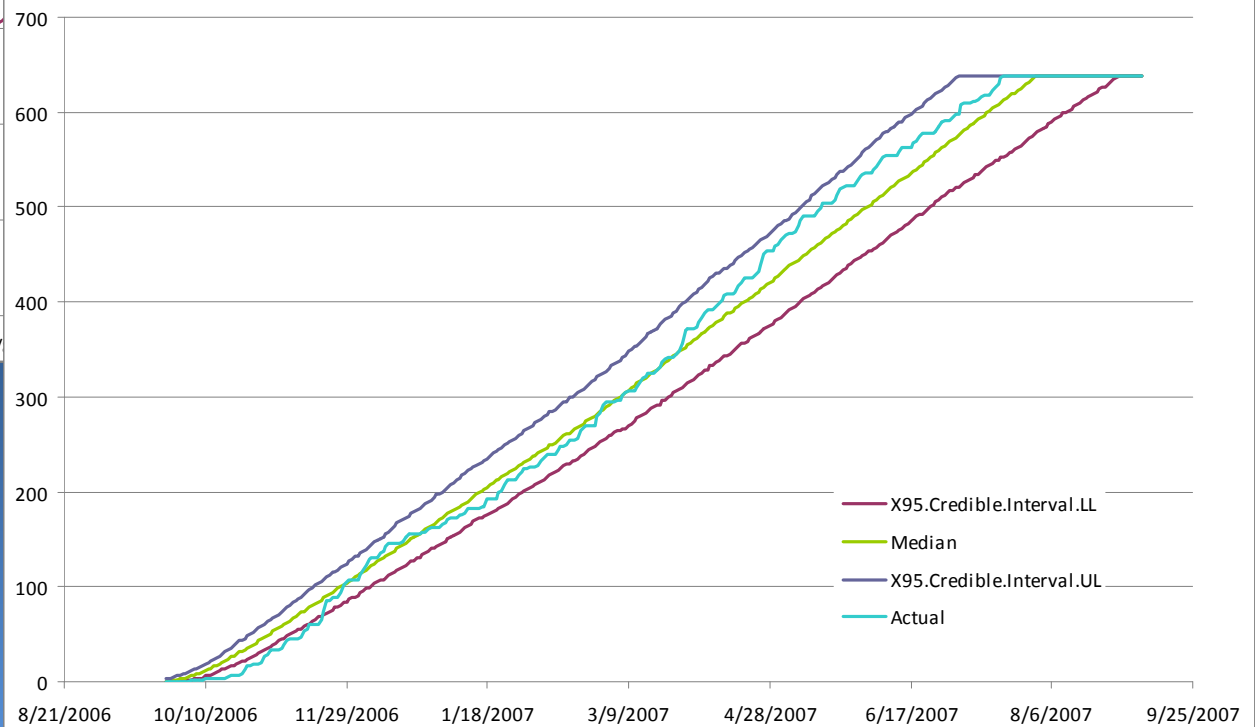
- Classify sites according to enrolment rates into high ( $\mu_i > 0.4$ ), medium ( $0.2 < \mu_i < 0.4$ ), and low ( $\mu_i < 0.2$ ) enrolling categories
- Put different Gamma priors for sites belonging to each of the three categories and combine predictions
- Simulations presented were performed for single country trials

# Prediction at time $t_0 = 0$ months

Trial1 : Unstratified Enrollment Prediction at t=0

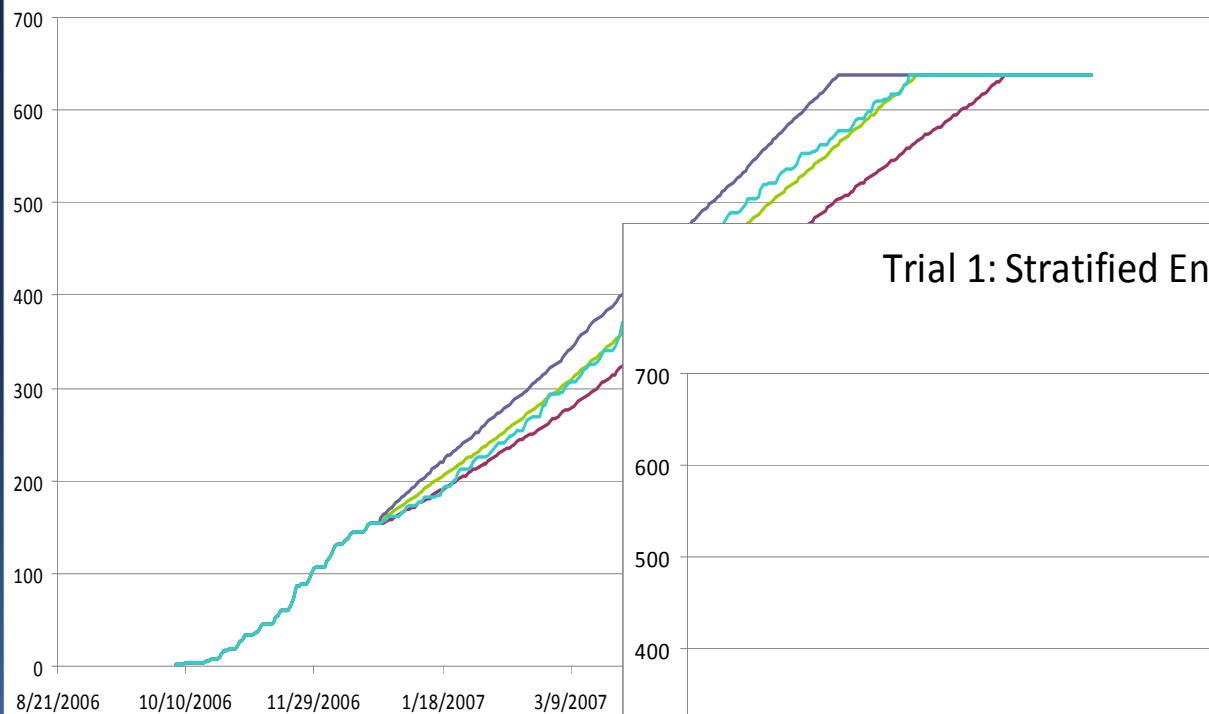


Trial 1: Stratified Enrollment Prediction at t=0

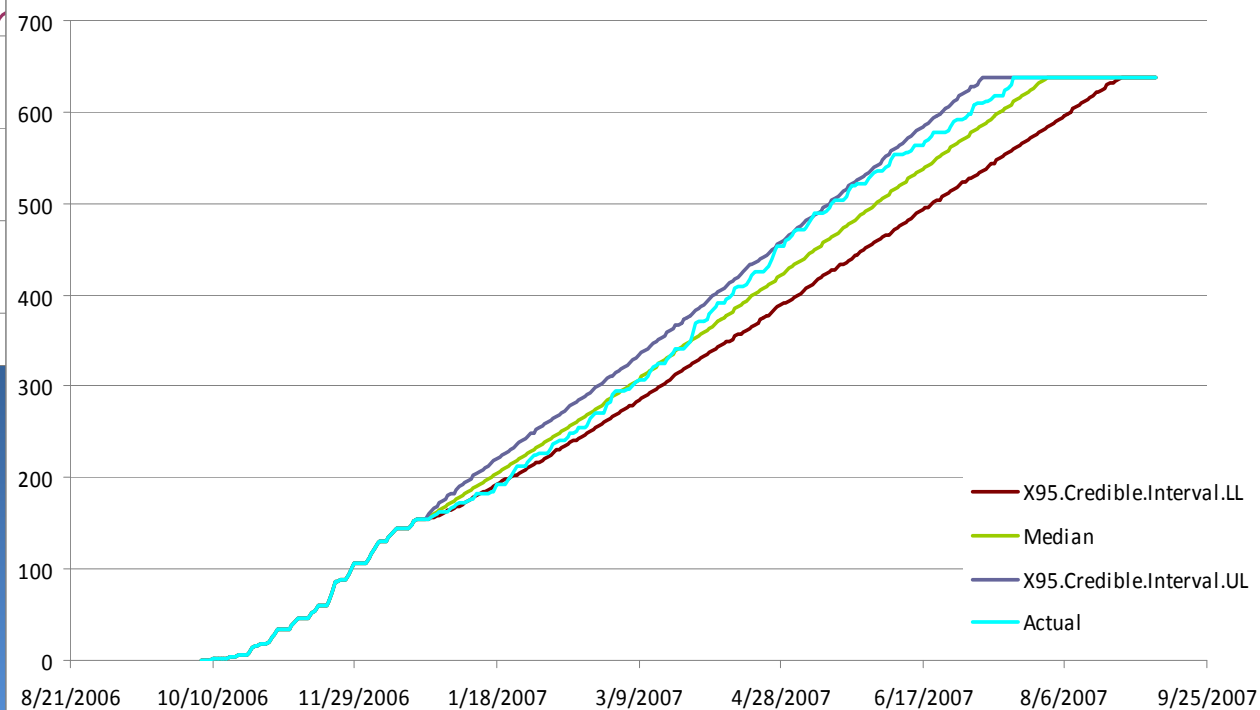


# Prediction at time $t_0 = 3$ months

Trial1 : Unstratified Enrollment Prediction at t=3

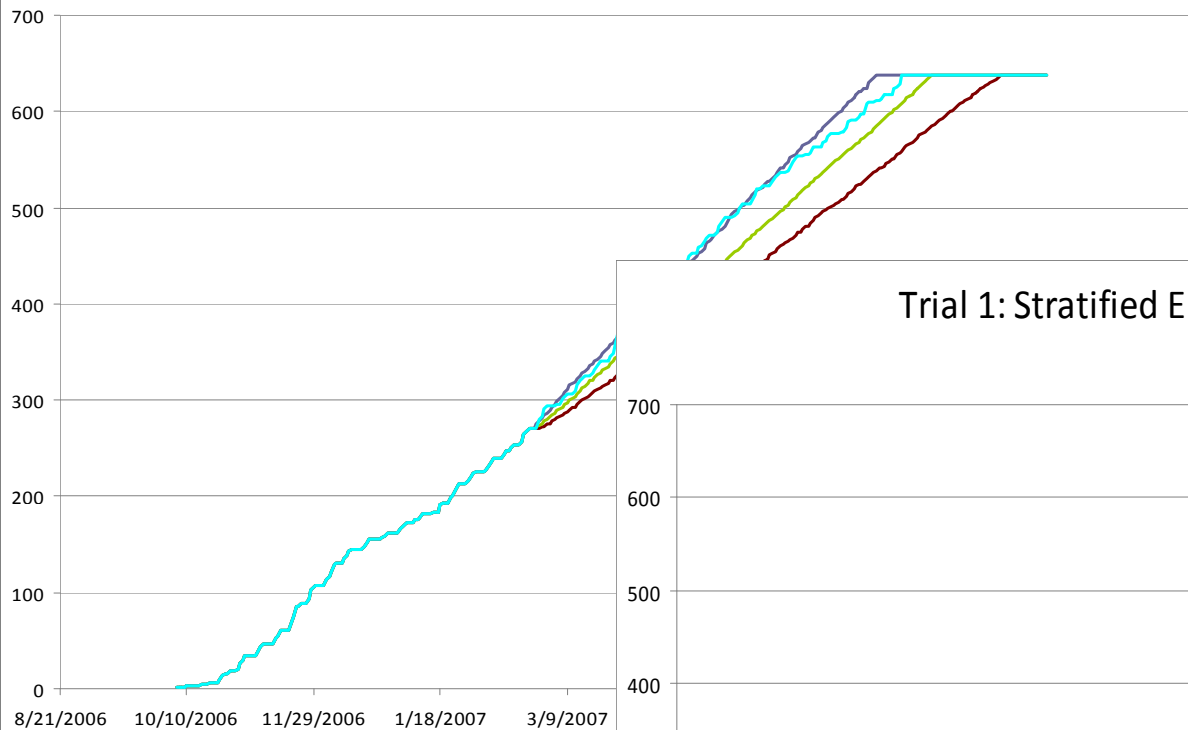


Trial 1: Stratified Enrollment Prediction at t=3

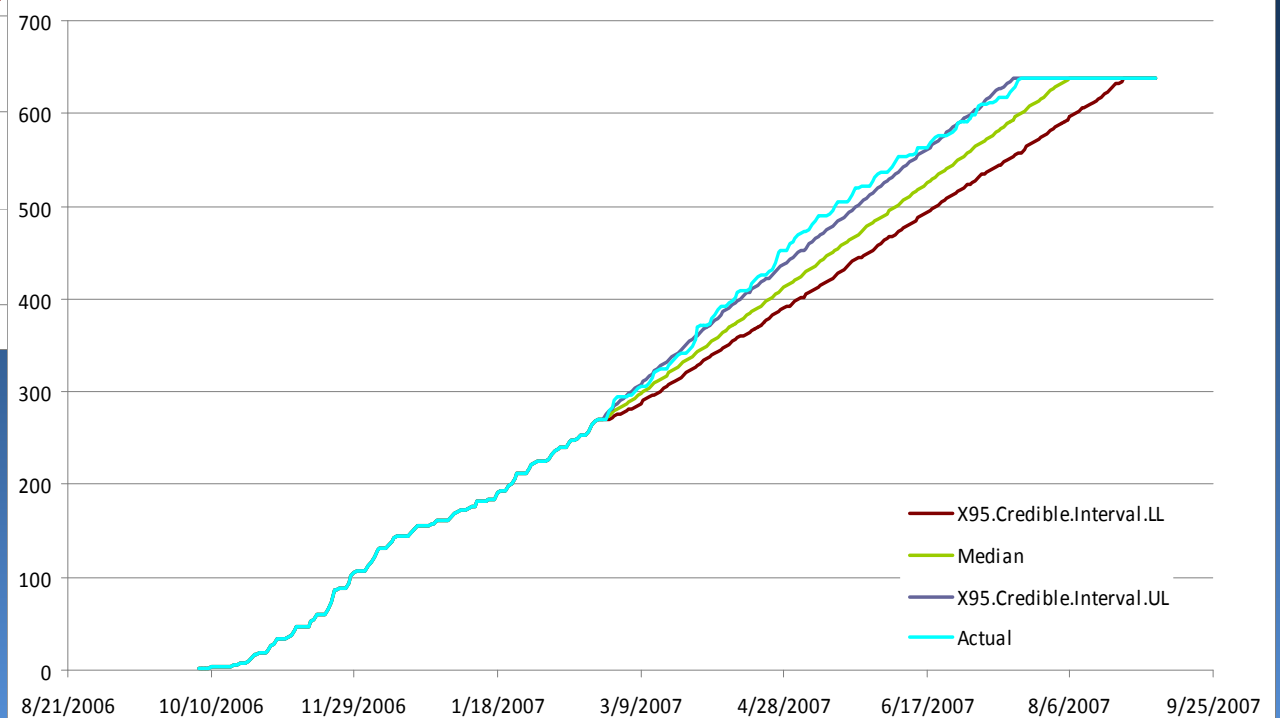


# Prediction at time $t_0 = 5$ months

Trial1 : Unstratified Enrollment Prediction at t=5

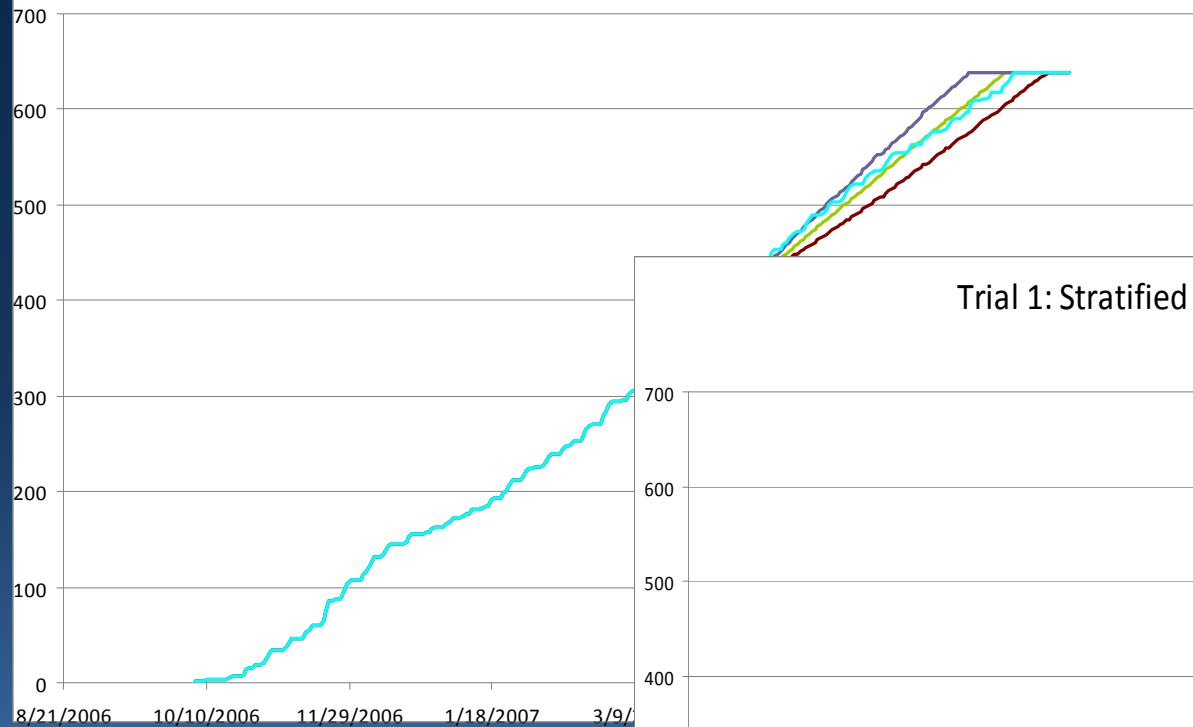


Trial 1: Stratified Enrollment Prediction at t=5

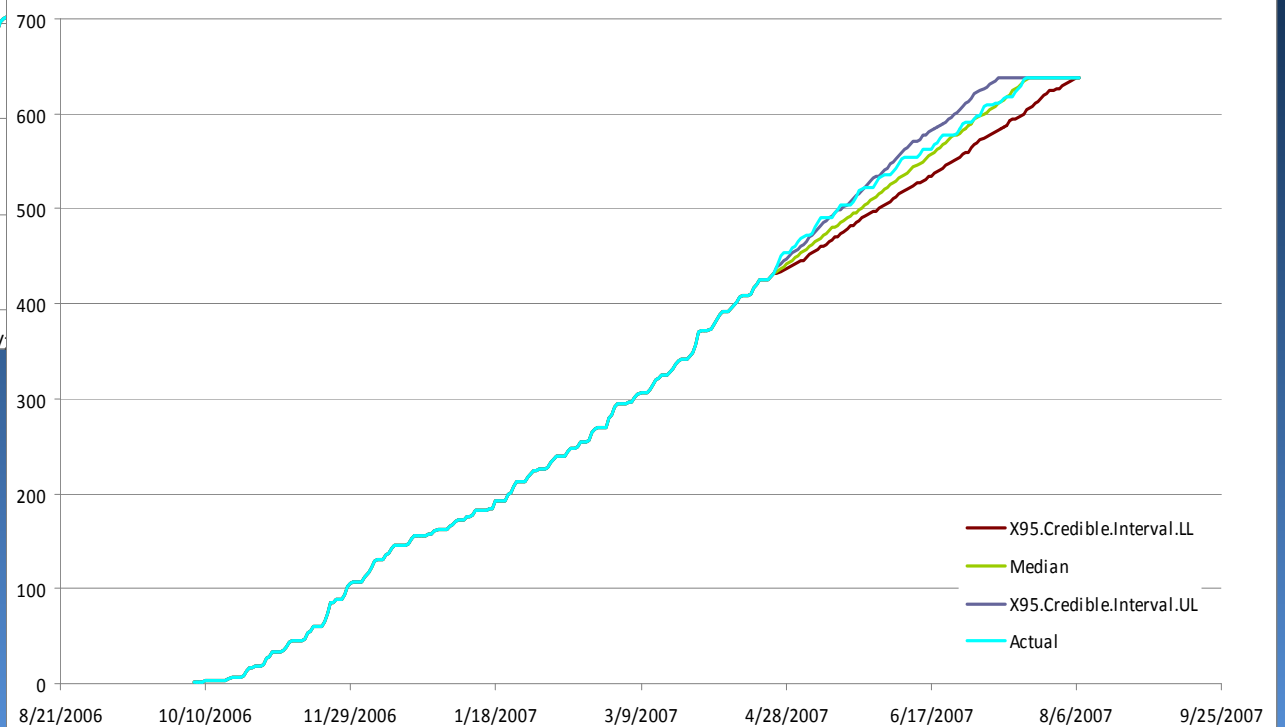


# Prediction at time $t_0 = 7$ months

Trial1 : Unstratified Enrollment Prediction at t=7



Trial 1: Stratified Enrollment Prediction at t=7



# Prediction times for a few other trials (in days)

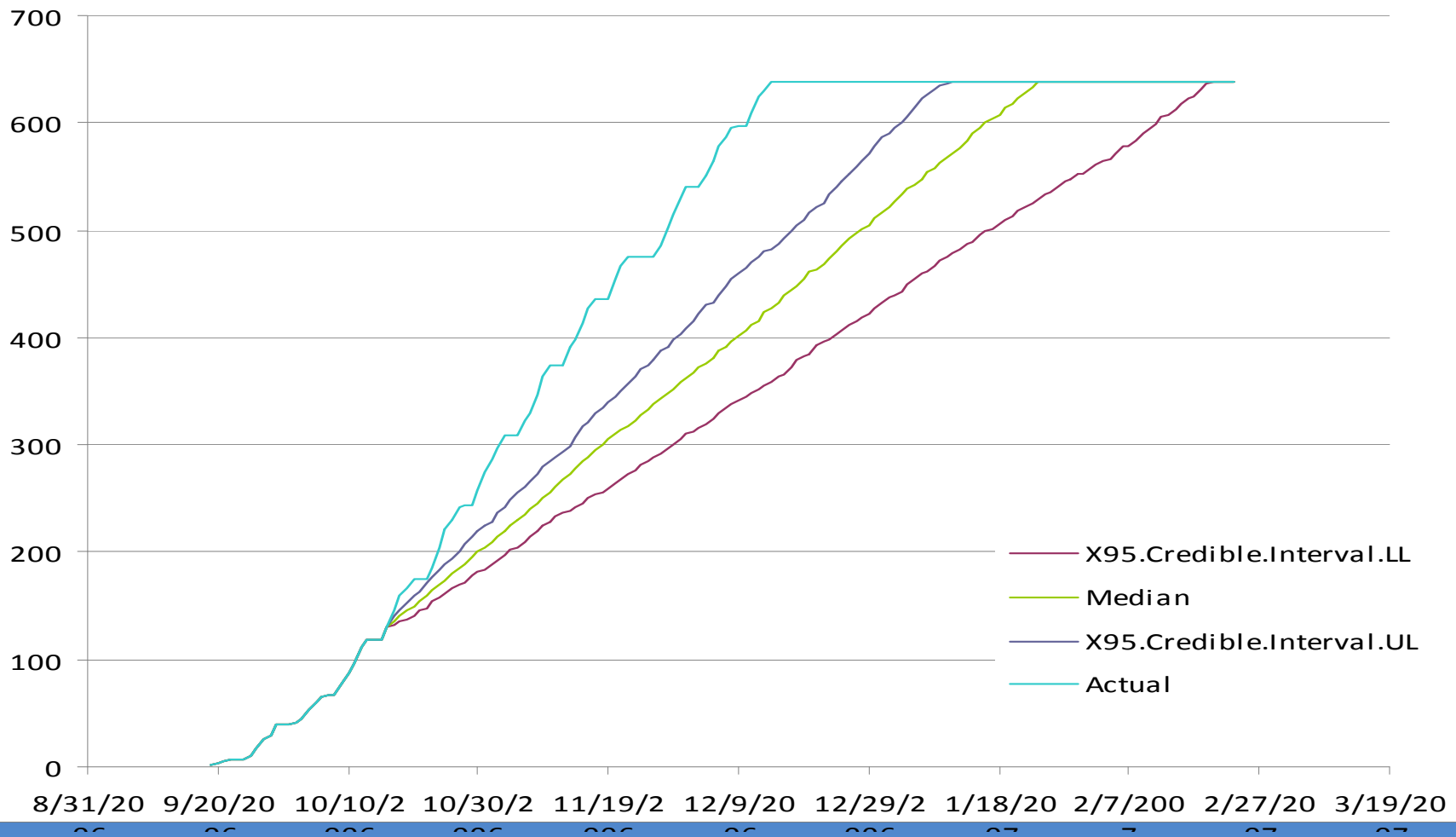
		<b>P2.5</b>	<b>Median</b>	<b>P97.5</b>	<b>Actual</b>
<b>Trial 1</b>	Stratified	281	308	338	297
	Unstratified	266	321	394	297
<b>Trial 2</b>	Stratified	147	164	186	153
	Unstratified	122	135	150	153
<b>Trial 3</b>	Stratified	131	145	163	134
	Unstratified	117	142	176	134
<b>Trial 4</b>	Stratified	309	317	326	304
	Unstratified	309	325	347	304

**Ignoring the first inter-arrival time**



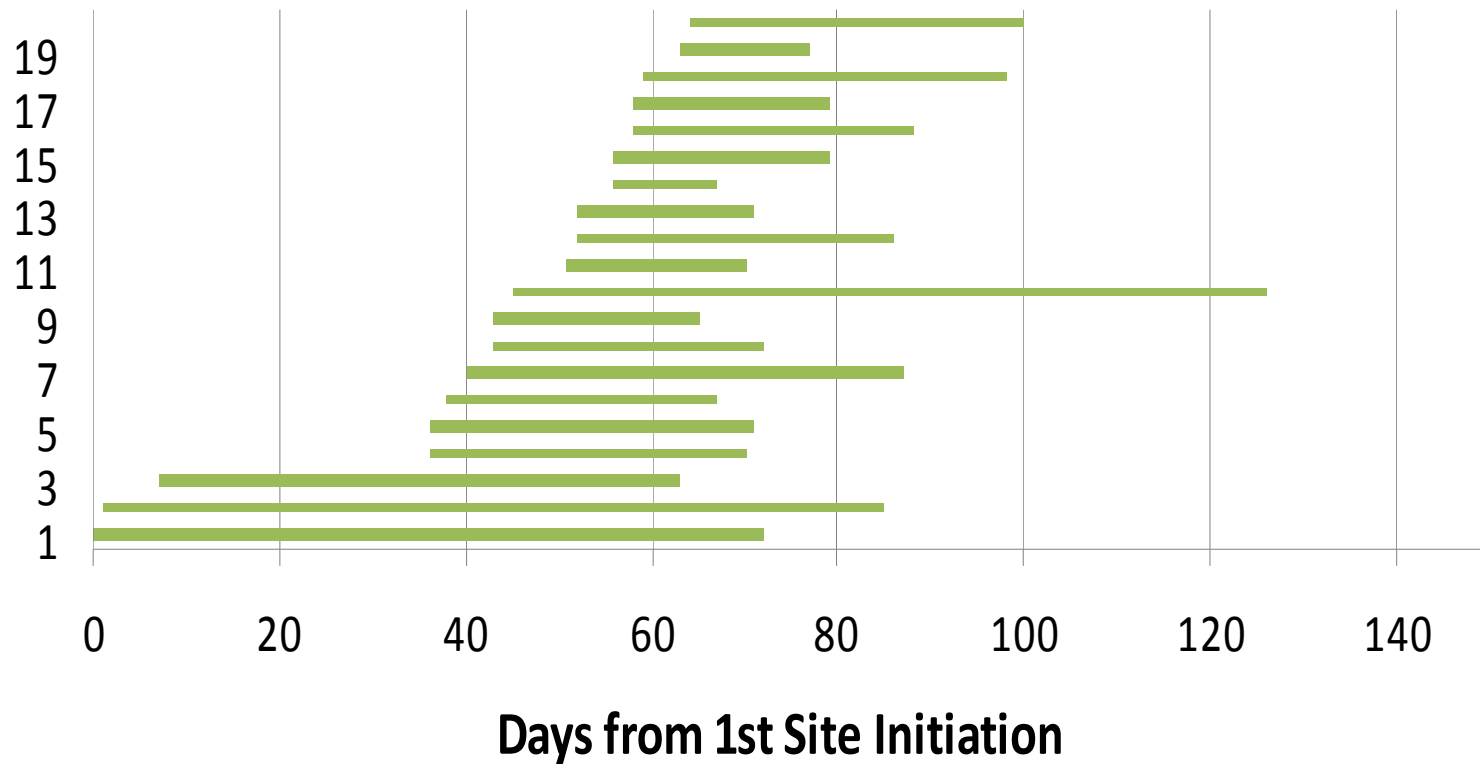
# Model breakdown #1

## Trial 6: Starting at SIV



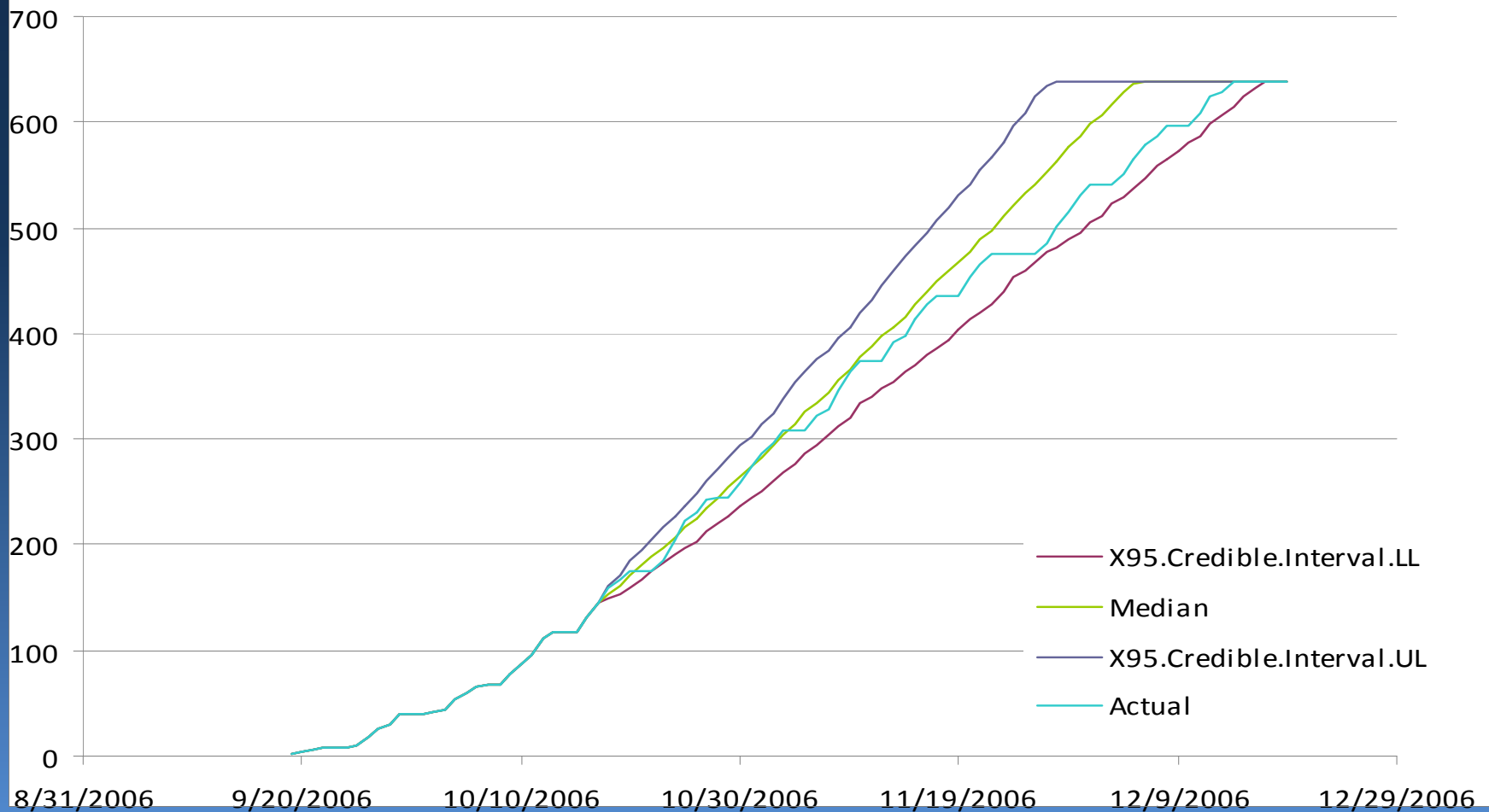
# Time from Site Initiation Visit to First Subject First Visit

## First 20 sites



# Prediction starting at FSFV

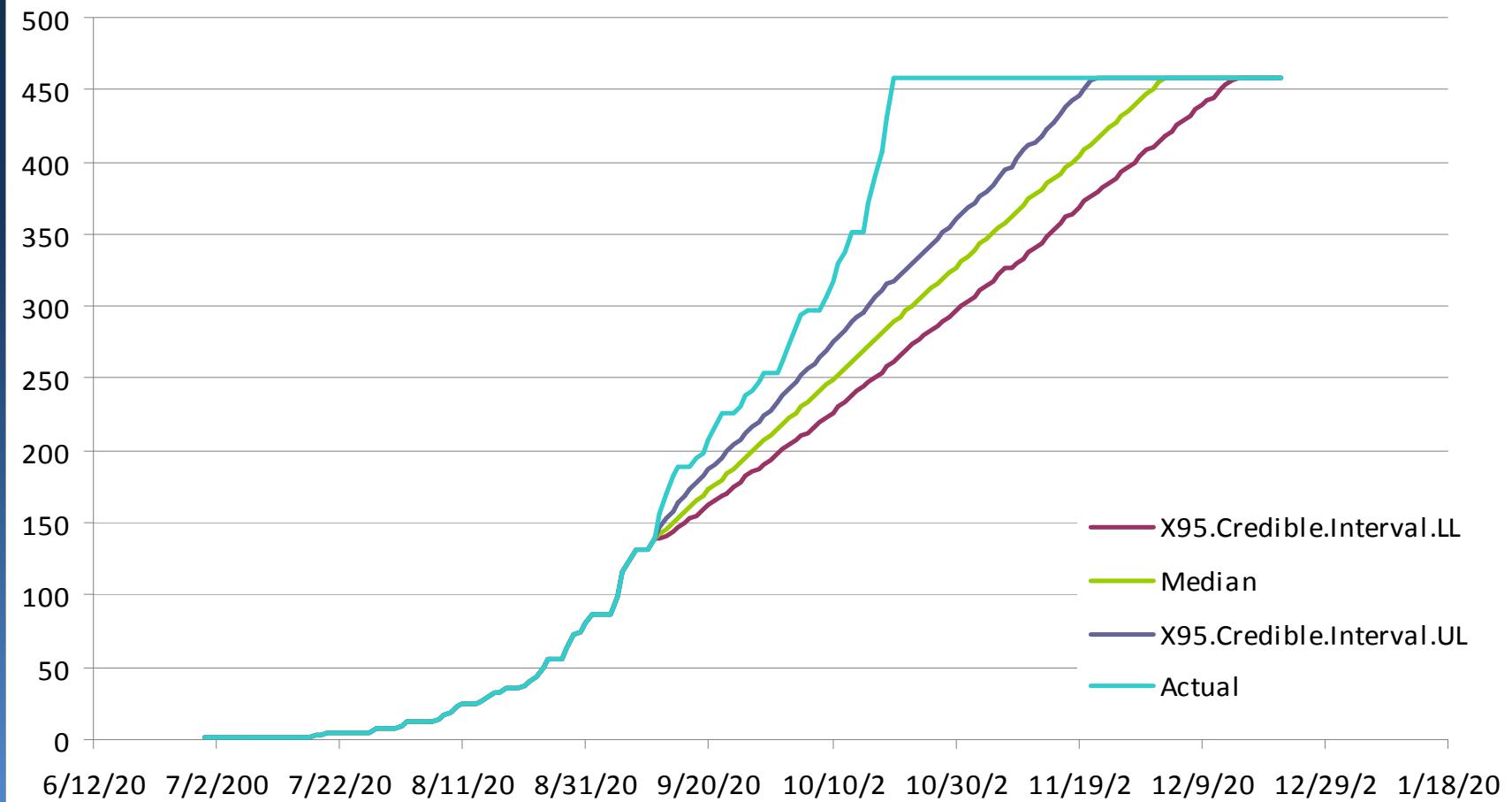
## Trial 6: Starting at FSFV



**Time-variant enrolment rates**

# Model breakdown #2

## Trial 7- no HF $\Omega$



# Time varying parameters

- Harvey and Fernandes (1989) proposed a model in the econometrics literature that modifies the Poisson-Gamma to allow the underlying mean of the process to change over time
- Parameters of Gamma change from time  $t-1$  to  $t$

$$a_t = \omega a_{t-1} \text{ and } b_t = \omega b_{t-1}$$

- Mean of the Poisson remains the same
- Variance is inflated by a factor  $1/\omega$  with  $0 < \omega < 1$
- $\omega$  is chosen to control the amount of drift

(Could be varied with  $t$  or modeled in some way as a function of past observations either as a numeric function or as parameter that is updated in a Bayesian manner)

# Model for drift in Gamma parameters

- Posterior at time **t-1** (Gamma):

$$G(\mu_{t-1}; \alpha_{t-1}, \beta_{t-1}) = \frac{\mu_{t-1}^{\alpha_{t-1}-1} e^{-\beta_{t-1}}}{\Gamma(\alpha_{t-1}) \beta_{t-1}^{\alpha_{t-1}}} \quad \alpha_{t-1}, \beta_{t-1} > 0$$

- Prior at time **t** (before observing  $n_t$ ):

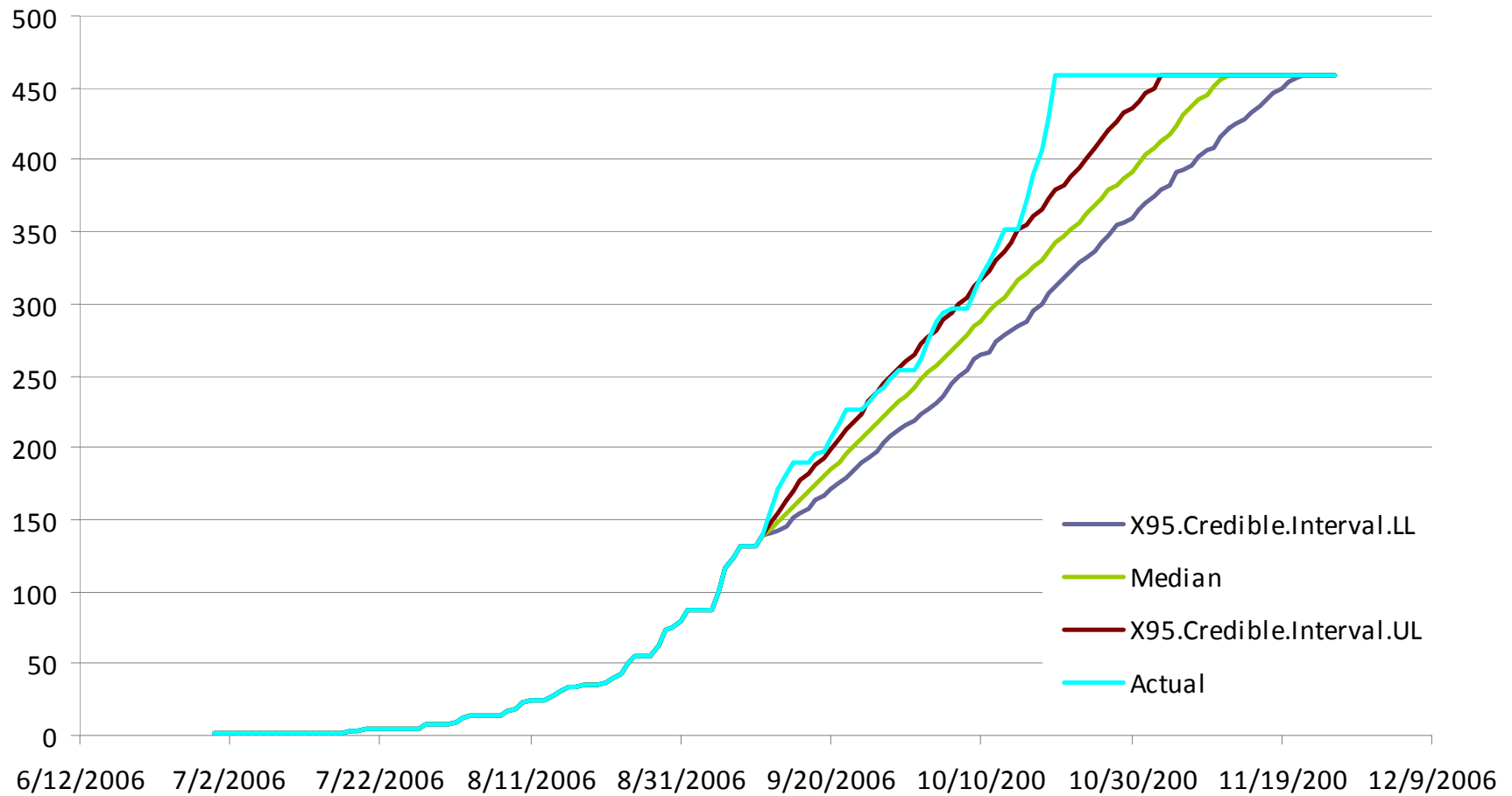
$$G(\mu_t; \alpha_{t|t-1}, \beta_{t|t-1}) = \frac{\mu_{t|t-1}^{\alpha_{t|t-1}-1} e^{-\beta_{t|t-1}}}{\Gamma(\alpha_{t|t-1}) \beta_{t|t-1}^{\alpha_{t|t-1}}} \quad \alpha_{t|t-1} = \omega \alpha_{t-1}, \beta_{t|t-1} = \omega \beta_{t-1} \quad 0 < \omega < 1$$

- Posterior at time **t-1** (after observing  $n_t$  in period **t**):

$$G(\mu_t; \alpha_t, \beta_t) = \frac{\mu_t^{\alpha_t-1} e^{-\beta_t}}{\Gamma(\alpha_t) \beta_t^{\alpha_t}} \quad \alpha_t = \alpha_{t|t-1} + y_t, \beta_t = \beta_{t|t-1} + 1$$

# Application of HF model to Trial 7

Trial 7-  $\Omega=.95$





# Conclusions

## Further extensions

- Incorporating important covariates into the model to monitor and predict appropriate representation of subpopulations and balance in randomization strata
- Predicting changes in enrolment patterns, acceleration of slowdown of enrolment at specific sites
- We have already incorporated event modeling into our software to predict timing of interim analyses and trial end in survival studies

# Some practical conclusions and suggestions

- Exclude or limit countries likely to have low recruitment in trial design
- Prioritize early initiation for countries likely to have high recruitment
- Drop countries that have not initiated sites within a certain time after several countries are recruiting at a good rate
  
- Identify attributes of low enrolling sites by analyzing past data
- Limit number of potentially low enrolling sites in trial design. Prioritize early initiation for sites likely to have high recruitment. Create “standby” list of sites.
- Monitor sites using a statistical model (similar in spirit to quality control charts in manufacturing). Drop sites that are recruiting below minimum performance levels. Add sites from standby list.
- Save cost of drug by redistributing supplies at dropped sites to other sites in the same country
- Evaluate effect of using fewer sites with greater resources allocated per site (e.g. advertising budget, training, clinical research associate time)

# Take home messages

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- Modeling, simulating and forecasting enrolment and the arrival of events can help a sponsor or CRO get a grip on the uncertainty inherent in trial timelines
- This quantitative exercise combines with the “art of patient recruitment and retention” to run more efficient and successful studies
- It can help track issues such as poor-performing countries or sites, and guide decisions such as when to open new sites, or how and when to resupply sites with drug
- Cost savings can be substantial if impact on NPV, drug supply chain, and site monitoring is taken into account and acted upon

# References

- Anisimov, V., and Fedorov, V. Modelling, prediction, and adaptive adjustment of recruitment in multicenter trials. *Statistics in Medicine*. 2007, 26: 4958-4975
- Harvey, A.C., and Fernandes, C. Time Series Models for Count or Qualitative Observations. *The Journal of Business and Economic Statistics*. 1989, 7:4:407-422.
- Lamberti, MJ. State of Clinical Trials Industry. Thomson Centerwatch. 2006, 292.
- Pierre, C. Recruitment and Retention. 2006.