SeDFAM: Semiconductor Demand Forecast Accuracy Model

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Semiconductor Industry

Industry Characteristics

- High Technology - Competition leads to
  Short Product Life Cycles and Frequent Line Width Changes
- Volatile Demand
- Fab financing: tool prices

Business Contribution: Quantify Risk and Uncertainty

- Capacity acquisition
  - Customer service: meet market demand
  - Tool utilization

Goals of the Research

- Forecast Modeling

  1. Covariances of product demands; substitutes - complements
  2. Signal deteriorating forecasts
  3. Forecast simulation

Demand Modeling

- A hierarchical model:
  Product families by general functionality, i.e. memory
  Products by functionality and line width, i.e. memory CMOS 12
- Level of detail driven by capacity planning
- For families with persistent demands
- Products have transient demands
- Family demands are often correlated: Memory and CPU chips
- Correlations can often be strong
  1. Correlation among the products of the same family
     e.g. between (memory,CMOS8) and (memory,CMOS10)
  2. Correlation among the products of different product families
     e.g. between (memory,CMOS10), (X86,CMOS10)

Notation

- p, q: families (e.g. ASICS, X86)
- tec , $tec+$: a line width and its successor (e.g. CMOS10, CMOS12)
- (p, tec): a product (e.g. (memory, CMOS10))
- $d_{s,t}^{p,tec}$: demand forecast made in s for t for a product (p, tec)
- $d_{s,t}^{p}$: demand forecast made in s for t for a family p

$$d_{s,t}^{p} = \sum_{tec} d_{s,t}^{p,tec}$$

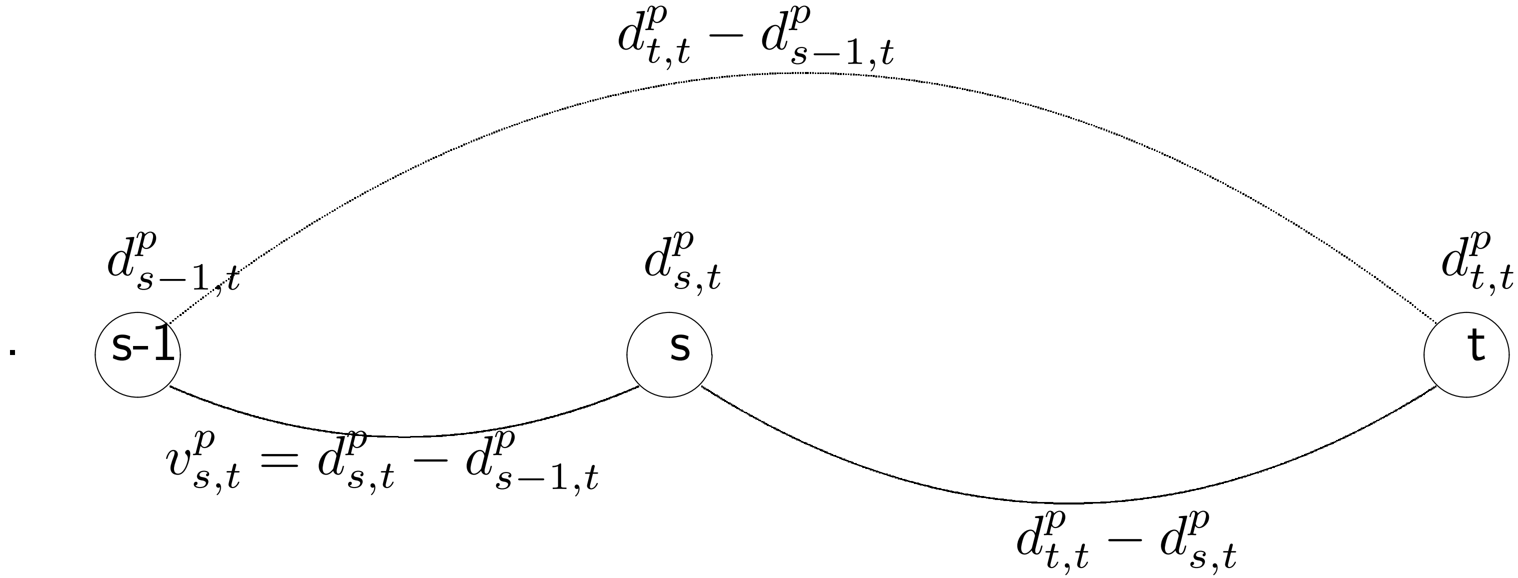
- H : forecast horizon

Inputs to Forecast Evolution

Forecast history for a product (p, tec)

$Lags$	Jan	.....	Sep	.....	Dec
0	$d^{p,tec}_{jan,jan}$	.....	$d^{p,tec}_{sep,sep}$	.....	$d^{p,tec}_{dec,dec}$
..	..	.....	.....	.....	.....
$t-s=2$	$d^{p,tec}_{nov,jan}$	.....	$d^{p,tec}_{jul,sep}$	.....	$d^{p,tec}_{oct,dec}$
..	..	.....	.....	.....	.....
H	$d^{p,tec}_{jan-H,jan}$	.....	$d^{p,tec}_{sep-H,sep}$	.....	$d^{p,tec}_{dec-H,dec}$

Heath-Jackson Framework for Family Demands



$v^p_{s,t}$ uncorrelated with $v^p_{s+1,t}$
Distribution of $v^p_{s,t}$ depends on $t - s$
$v^p_{s,t}$ correlated with $v^q_{s,r}$
$v_s = [v^p_{s,t}]$: Family forecast update vector at time s

SeDFAM

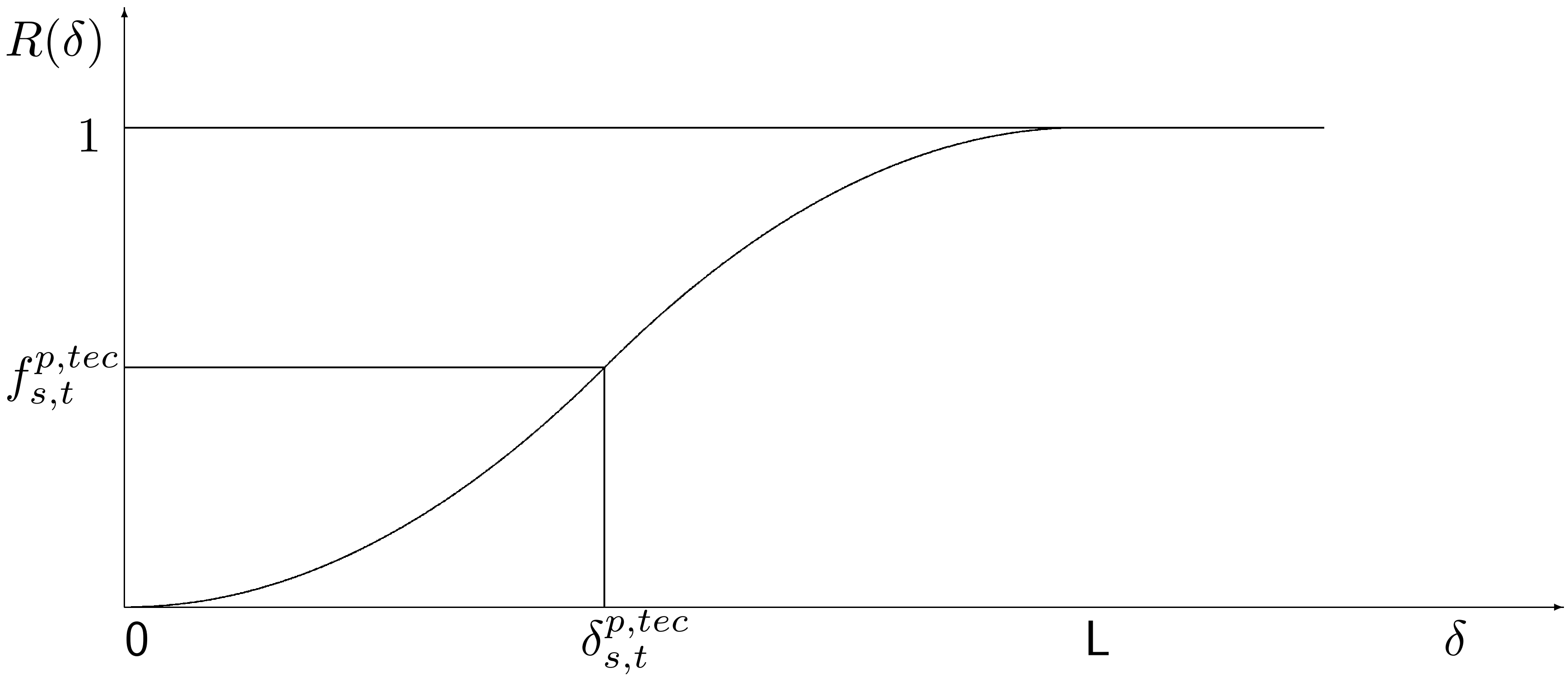
Fractional Forecasts: $f_{s,t}^{p,tec}$: Fraction of demand for family p line width tec or shorter, forecasted from s for t

$$f_{s,t}^{p,tec} = \frac{\sum_{linewidth \leq tec} d_{s,t}^{p,tec}}{d_{s,t}^{p}}$$

Analyzing Fractional Forecasts

- Heath-Jackson approach is not directly applicable
- Apply a nonlinear transformation mapping Fractional Forecasts to Perceived Ages
- Apply Heath-Jackson to Perceived Age Forecasts

Computing Perceived Ages from Fractional Forecasts



Perceived age update $u_{s,t}^{p,tec} = \delta_{s,t}^{p,tec} - \delta_{s-1,t}^{p,tec}$

Perceived Age Update Vectors

- Construct iid update vectors

$$u_s^{14} = [u_{s,s}^{X86,14}, ..., u_{s,s+H-1}^{X86,14}, u_{s,s}^{Mem,14}, ..., u_{s,s+H-1}^{Mem,14}, u_{s,s}^{PPC,14}, ...]$$

iid: updates for different technologies are independent

$$u_s^{16} = [u_{s,s}^{X86,16}, ..., u_{s,s+H-1}^{X86,16}, u_{s,s}^{Mem,16}, ..., u_{s,s+H-1}^{Mem,16}, u_{s,s}^{PPC,16}, ...]$$

iid: updates created in different time periods are independent

$$u_{s+1}^{16} = [u_{s+1,s+1}^{X86,16}, ..., u_{s+1,s+H}^{X86,16}, u_{s+1,s+1}^{Mem,16}, ..., u_{s+1,s+H}^{Mem,16}, u_{s+1,s+1}^{PPC,16}, ...]$$

- Data is missing if $(X86, 16)$ production ends before $s + H$
- $u_s^{tec} \sim N(0, \Sigma)$, use EM (Expectation Maximization) algorithm by Schafer (1997)

Summary: SeDFAM Estimation Procedure

Inputs : Demand forecasts, $d_{s,t}^{p,tec}$
1. Estimate family forecast update covariance matrix, $\hat{\Lambda}$ *2. Fit ramp function* $\hat{R}$ *to fractional forecasts* *3. Compute perceived age forecasts* $\delta_{s,t}^{p,tec} = \hat{R}^{-1}(f_{s,t}^{p,tec})$ *4. Estimate perceived age forecast update covariance matrix,* $\hat{\Sigma}$ *(using the EM algorithm)*
5. Use $\hat{R}$, $\hat{\Lambda}$, $\hat{\Sigma}$ *to compute variances and covariances of demands as seen in period* r

Step 5 of SeDFAM Estimation Procedure

- Computing variance of $R(\delta_{s,t}^{p,tec})$ is complicated because R is not linear
- Options: Monte-Carlo Sampling or Numerical Integration
  - R is a quadratic spline with 3 knots
  - Knots define regions of integration in $\Re^2$
- We use Monte-Carlo Sampling

Flowchart for Simulating Forecasts

Test accuracy of SeDFAM in estimating capacity demand covariances

Perceived Ages
$\delta_{r,t}^{p,tec} = \Delta_{r,t}^{p,tec} | \Im_r.$

Family Demands
$d_{r,t}^{p} = D_{r,t}^{p} | \Im_r.$

Perceived Age Updates
$U_s^{tec} = (U_{s,t}^{p,tec}) \sim N(0, \Sigma).$

Family Demand Updates
$V_s = (V_{s,t}^{p}) \sim N(0, \Lambda).$

Perceived Age Forecasts $\Delta_{s,t}^{p,tec} = \Delta_{s-1,t}^{p,tec} + U_{s,t}^{p,tec}.$

Family Demand Forecasts $D_{s,t}^{p} = D_{s-1,t}^{p} + V_{s,t}^{p}.$

Fractional Demand Forecasts $F_{s,t}^{p,tec} = R(\Delta_{s,t}^{p,tec})$

Product Demand Forecast $D_{s,t}^{p,tec} = D_{s,t}^{p}(F_{s,t}^{p,tec} - F_{s,t}^{p,tec+})$, see (**??**).

Biases

- Lag bias: $E(update) \neq 0$, simple modification of forecast evolution

- Nonlinearity bias: Fractional forecasts $= R$ (perceived ages)
  perceived ages unbiased implies fractional forecasts biased
  Small when R is close to linear.

Capacity Demanded from a Critical Tool

- A critical tool
- Used for technologies $tec = 10$ and $tec = 12$, and for families A and B
- Consider capacity demands for a critical tool with processing times, $c^{p,tec}$

	$tec = 10$	$tec = 12$
A	1.0	1.3
B	0.7	1.0

Experimental Design

Simulation Model

Historical Forecasts up to period now

Estimated covariance matrix
of forecasts generated in now

N independent evolutions
from period now on

True covariance matrix
of forecasts generated in now

Heuristics

- Allocation: Family variances are allocated to technologies
  - Proportional to forecasted volume

- Proportion: Update is proportional to the forecast

$$\frac{d^{p,tec}_{t-h,t} - d^{p,tec}_{t,t}}{d^{p,tec}_{t-h,t}} \sim \xi_h$$

  - Assume ξ_h , $h = 1..H$ has the same distribution for $\forall$ (p, tec) $\forall$ t
  - [Variance of error in $d^{p,tec}_{t,t}$] $= (d^{p,tec}_{now,t})^2 var(\xi_{t-now})$

- Neither Allocation nor Proportion capture correlations (time-wise or among families)

Results: Capacity Acquisition

- Customer Service: P(meet customer demand) targeted at 84.1 %.

Method	LT=2	LT=4	LT=6	LT=8	LT=10	LT=12	Aver
SeDFAM	83.2	82.6	83.0	83.0	83.5	83.9	0.97
Allocation	76.6	78.1	78.5	79.1	79.7	80.0	5.52
Proportion	86.2	85.4	88.2	87.2	86.8	88.2	3.29

- Tool Utilization : E(excess capacity / mean demand for capacity)

Method	LT=2	LT=4	LT=6	LT=8	LT=10	LT=12	Aver
True	22.9	34.4	33.6	35.5	33.9	33.1	-
SeDFAM	22.1	32.8	33.0	34.5	33.4	32.8	1.1
Allocation	18.8	29.1	28.5	30.5	29.5	29.1	5.4
Proportion	32.8	38.5	40.7	40.7	37.8	38.5	11.4

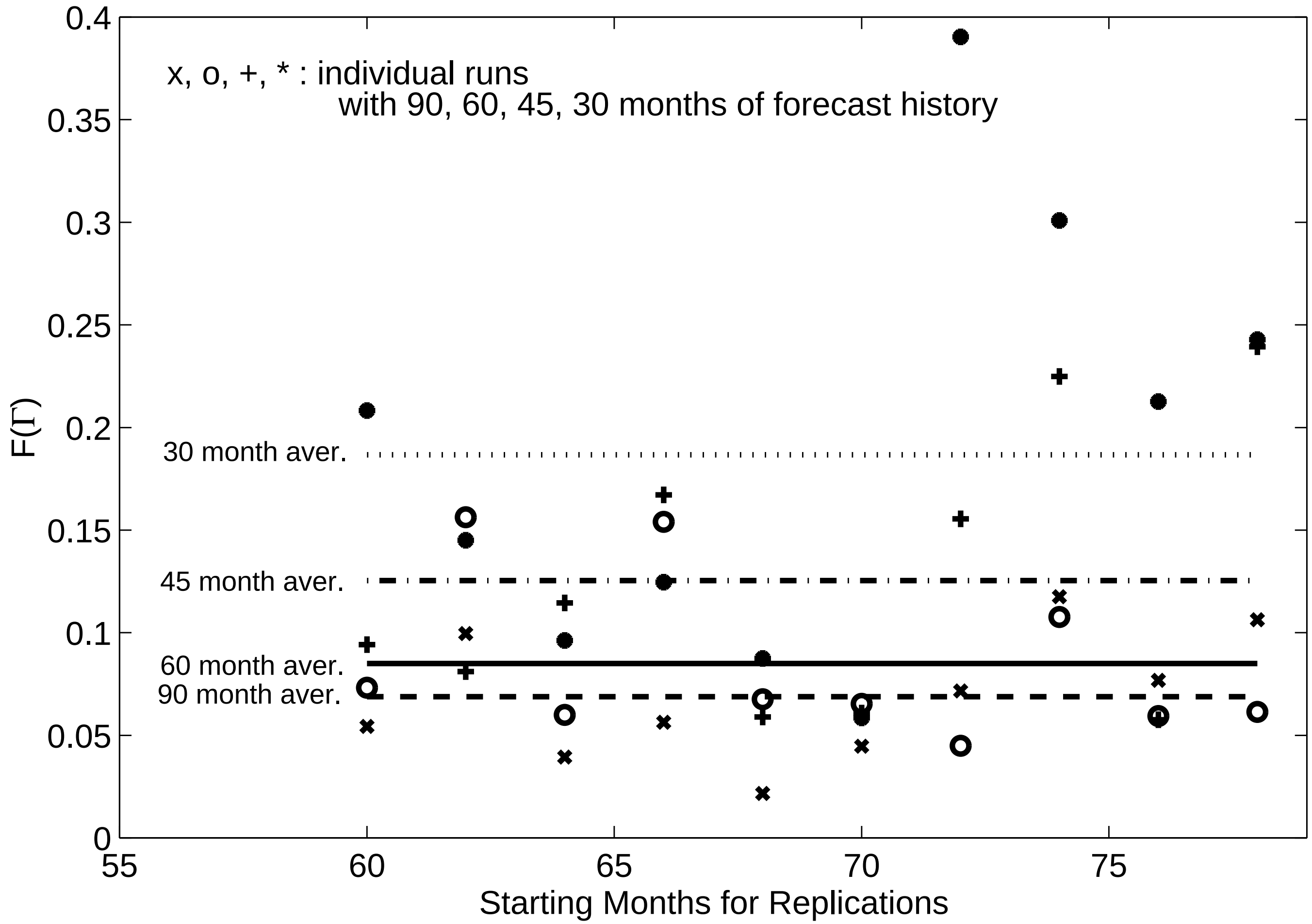
Robustness Analysis

- $C_{s,t}$: forecast (from s for t) of the critical tool capacity required
- Γ: covariance matrix of $[C_{now+1,now+1}, ..., C_{now+H+1,now+H+1}]$
- Performance measure: $F(\Gamma) = \frac{(Estimated\ \Gamma) - (True\ \Gamma)}{(True\ \Gamma)}$

Properties varied without significant effect on performance:

- Skewness of ramp curves
- Forecast horizon, H
- Magnitude of covariances in perceived age updates
- Correlations across families & time in family demand & age updates

Robustness Analysis: Forecast History

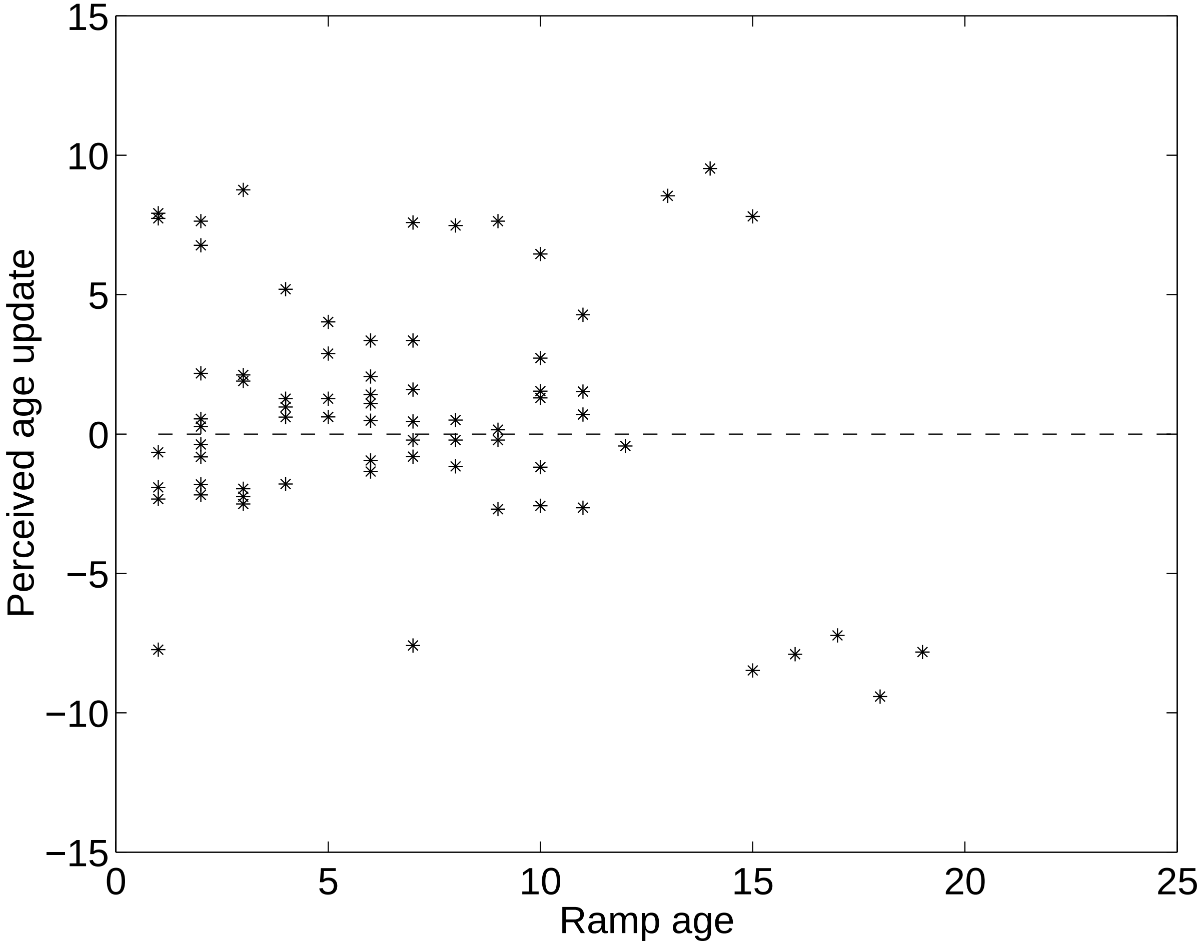


SedFAM estimates Γ more accurately with longer forecast history

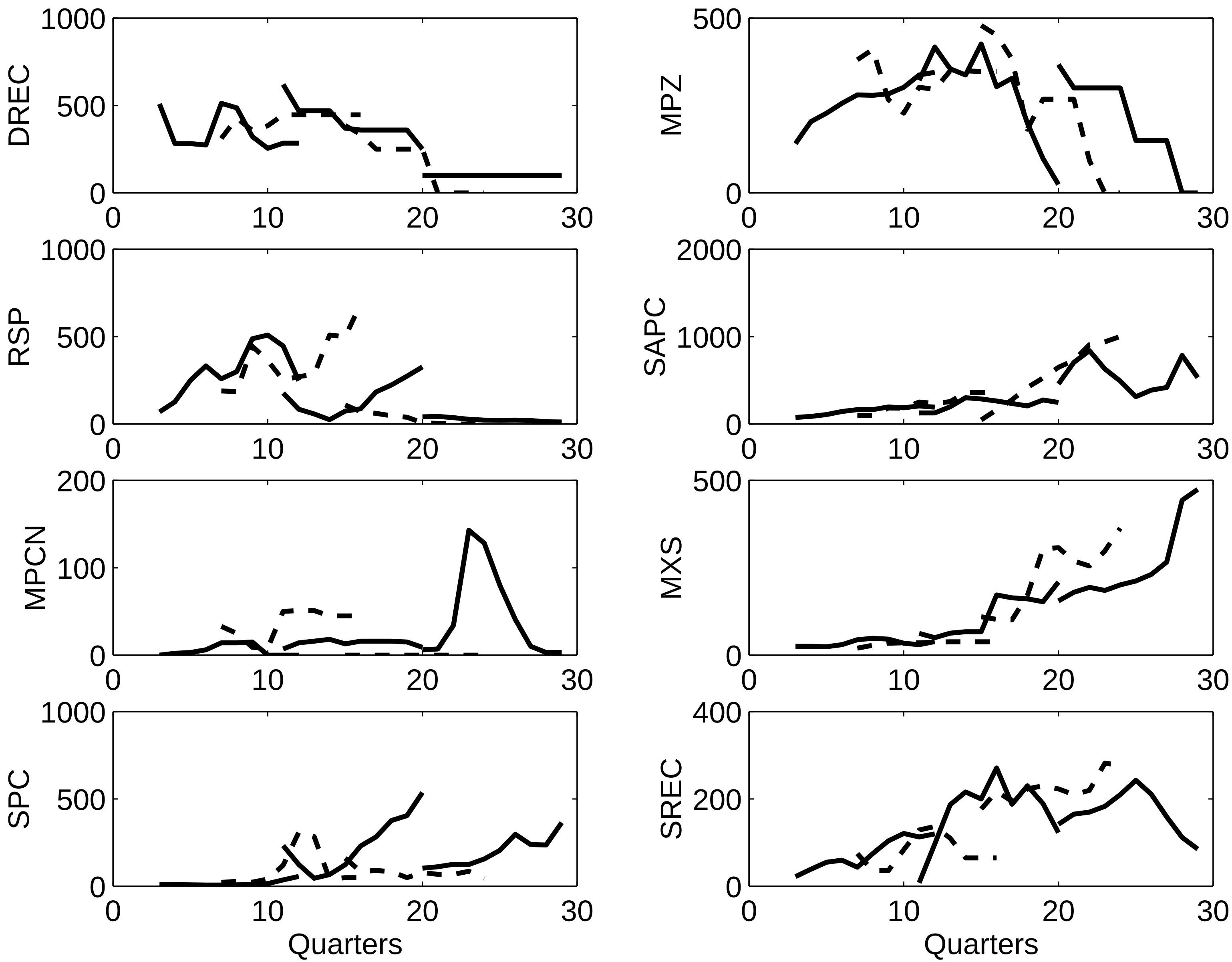
Tests with Industrial Data

Model assumptions pass statistical tests with the industrial data

Perceived age stationarity tested visually:



Product Family Demands



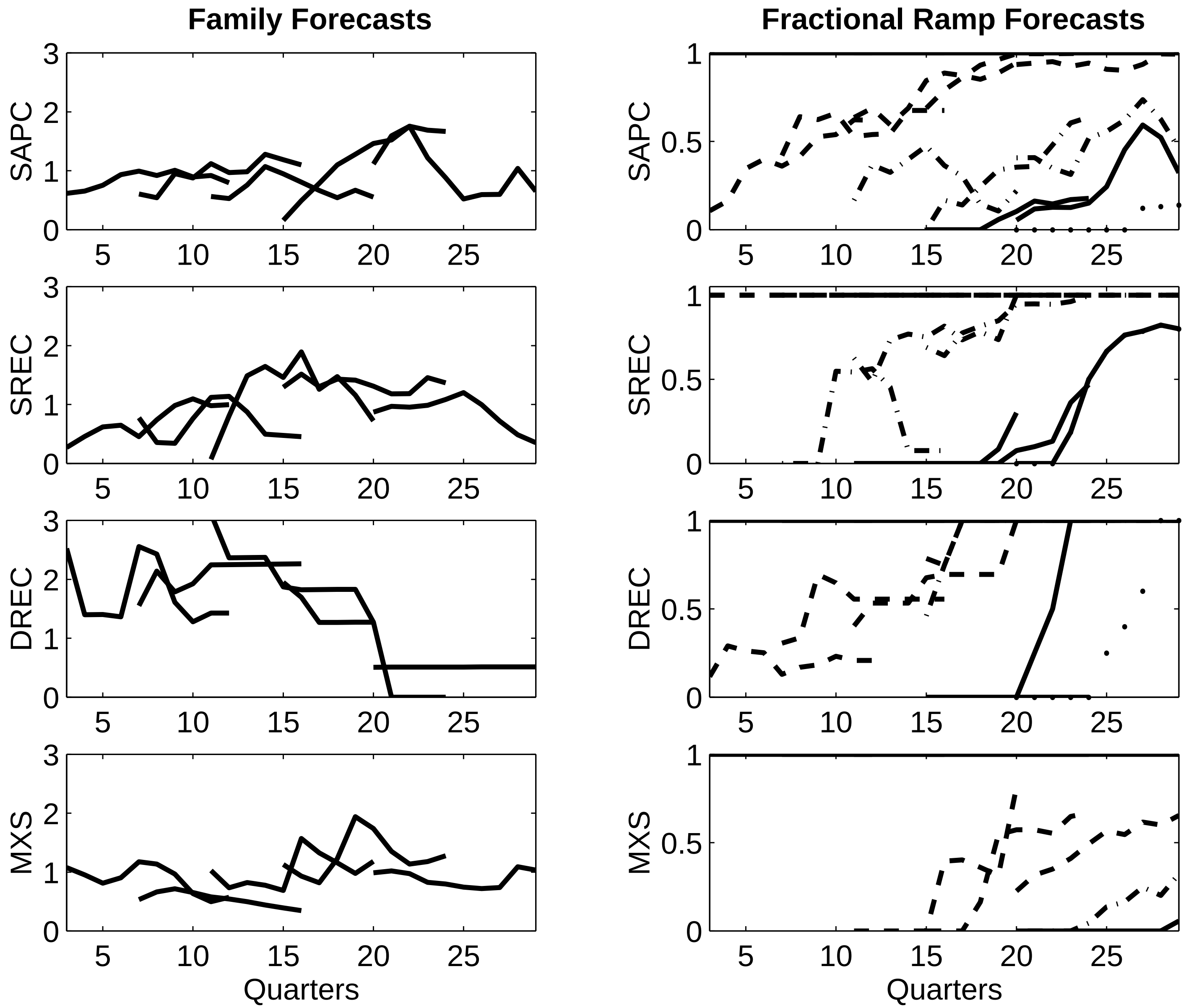
Data Analysis

- Select Families: SAPC, SREC, DREC, MXS
  - Life Cycles for MPZ, RSP ended
  - Life Cycles for MPCN, SPC started

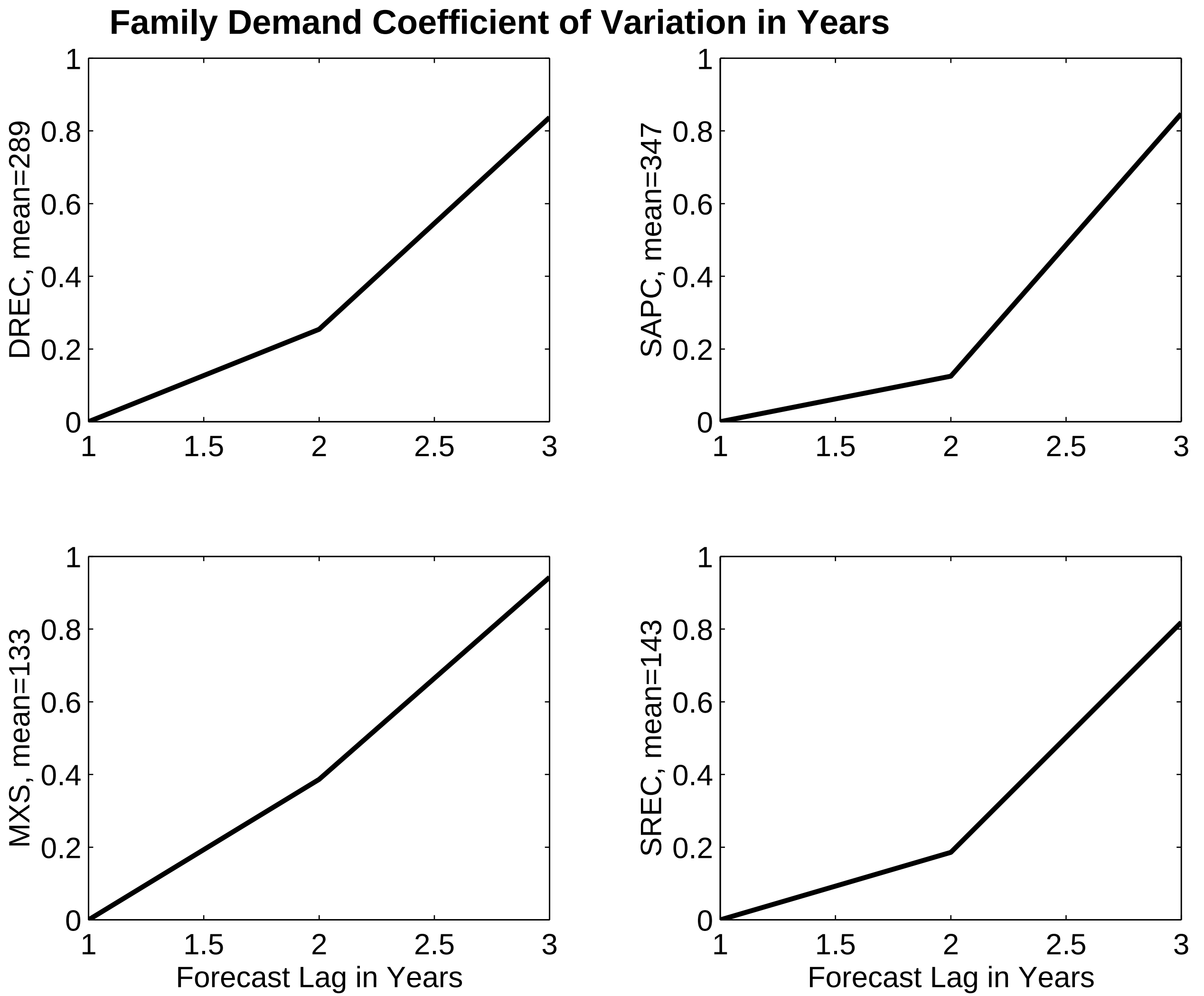
- Make demand stationary

Family	SAPC	SREC	DREC	MXS
Exponent	0.076	0.043	-0.0016	0.1192

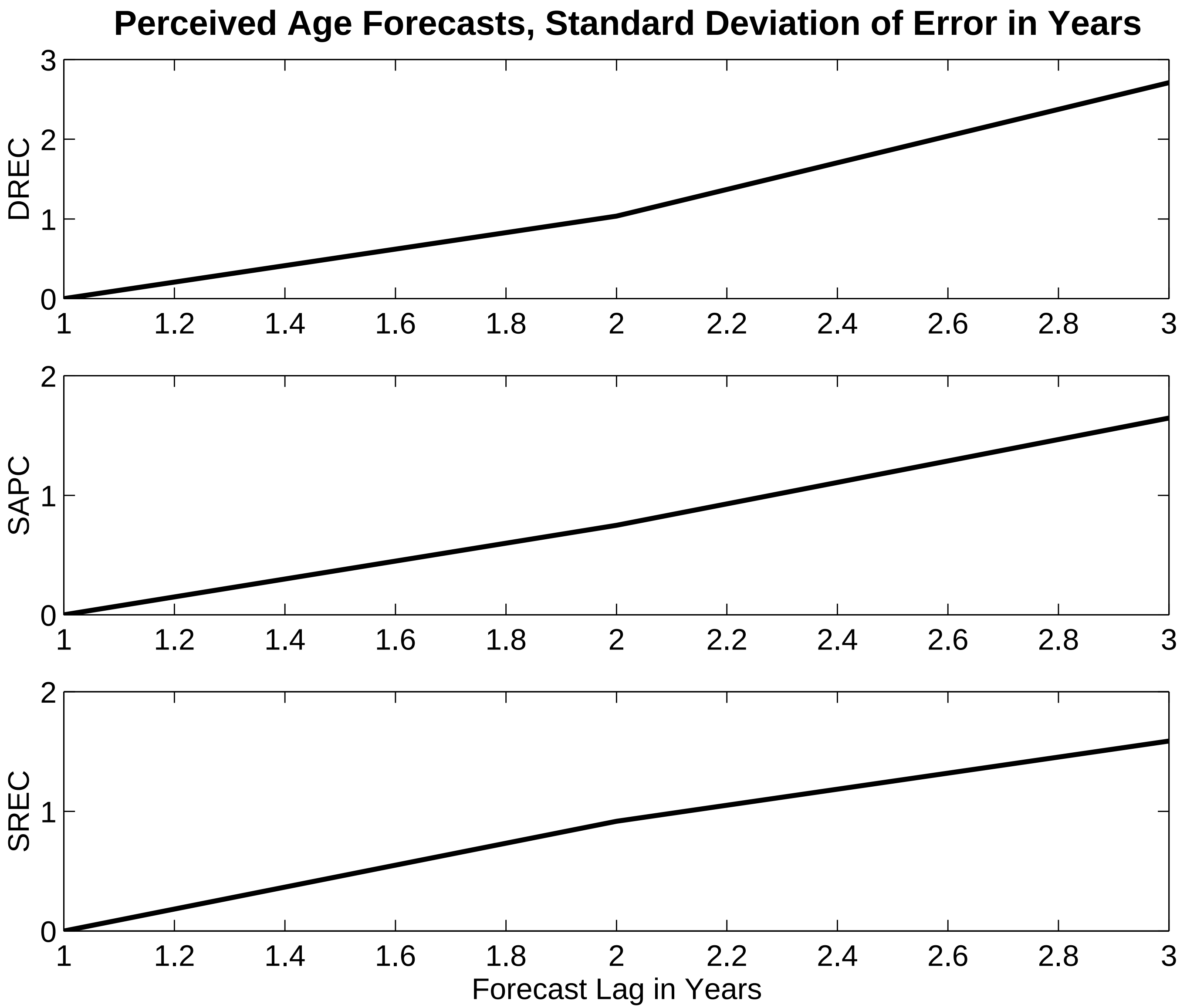
Family and Fractional Forecasts



Resolution of Uncertainty in Family Forecasts



Resolution of Uncertainty in Perceived Age Forecasts



Correlations in Family Demands

	DREC		SAPC		MXS		SREC	
	1	2	1	2	1	2	1	2
DREC-1	100		**-91**		73		74	70
DREC-2		100			-61	-75	-66	-67
SAPC-1	**-91**		100		-85	-70	-81	-81
SAPC-2				100				
MXS-1	73	-61	-85		100	**96**	**99**	**100**
MXS-2		-75	-70		**96**	100	**95**	**97**
SREC-1	74	-66	-81		**99**	**95**	100	**100**
SREC-2	70	-67	-81		**100**	**97**	**100**	100

DREC and SAPC subtitutes. MXS and SREC complements.

Correlations in Perceived Ages

	DREC		SAPC		SREC	
	1	2	1	2	1	2
DREC-1	100	61	-72			
DREC-2	61	100			-83	
SAPC-1	-72		100	55		
SAPC-2			55	100	-54	-57
SREC-1		-83		-54	100	
SREC-2				-57		100

Effectiveness of SeDFAM in estimating Γ, in %

- All key assumptions are statistically verified
- Correlations: Strong or weak
- Update Frequency
  - Only impacts SeDFAM performance thru amount of data available
  - Bayesian approach; Computationally stable, but sensitive to prior

	Sample size Λ, Σ	Size of Λ, Σ	$F(\Gamma)$ by Quarters 30	32	34	36	38	40	Aver $F(\Gamma)$
Annu,Quar,Bay.	5 , 10	10x10	63	51	35	37	40	42	44.7
Semi,Quar,Bay.	10 , 22	14x14	44	39	28	27	29	38	34.2
Quar,Quar,Bay.	20 , 50	16x16	44	32	32	29	30	27	32.3
Quar,Quar,Fre.	20 , 50	16x16	21	18	15	14	11	13	15.3

Conclusion

SeDFAM

- accurately estimates forecast error variances & correlations
- is robust
- requires about 48 periods of history for good performance
- benefits
  1. quantify risk and uncertainty
  2. signals deteriorating forecasts
  3. forecast simulation