Traffic Variations and their Influence on Performance

Temporal Disaggregation of Volatility for ATM Benchmarking

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Agenda

1) Motivation
2) Metrics
3) Influence on Performance
4) Conclusion

Motivation

Demand for Air Navigation Services in Europe

One of the busiest airspaces in the world:

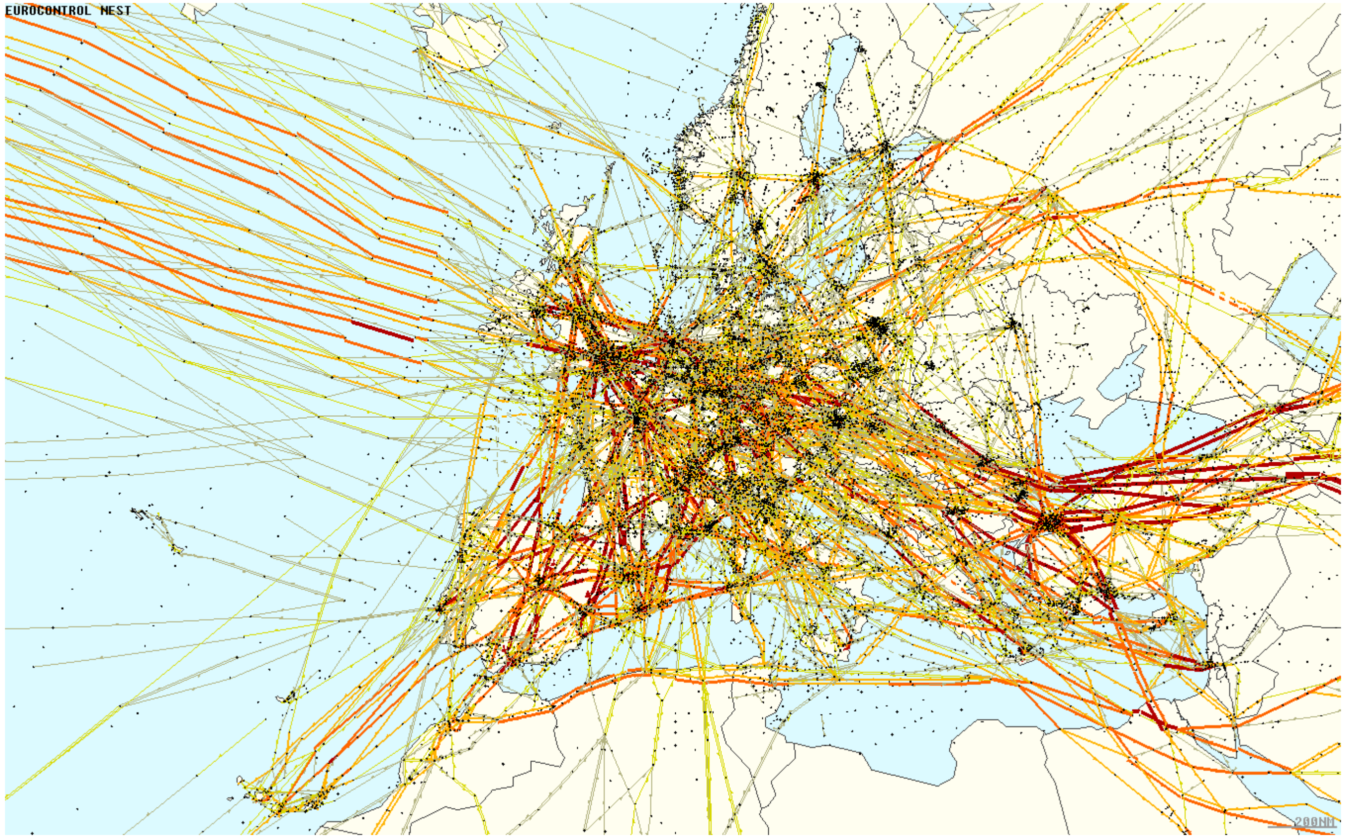
- 30,123 flights per day on average (2019),
- Peak: 36,913 flights per day (2019).

Spatial distribution:

- Hot spots especially in the core area,
- Low demand in the north and northeast Europe.

Challenges:

- Seven large hubs within a diameter of 1,000km.
- Traffic flow and distribution are **volatile**, e.g., due to weather/environment, political crises, pandemics, or strikes. → Low predictability.
- In the future: New entrants such as drones, UAVs, etc.



Source: NEST

Motivation

How is it managed?

Air Navigation Service Providers (ANSPs):

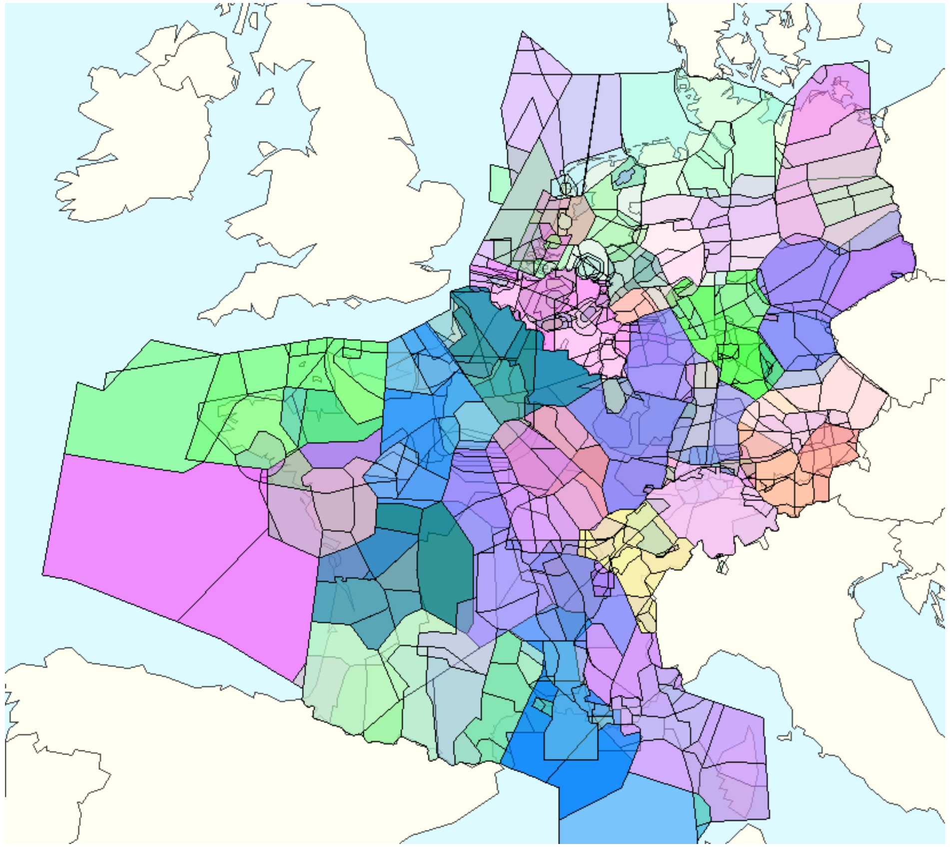
- ANSPs are responsible for safe and efficient air traffic operations.
- Main Trade-off: Costs versus Capacity.

Fragmented Airspace:

- 38 Air Navigation Service Providers (ANSPs),
- 63 Area Control Center (ACCs),
- A large number of sectors.

High level of heterogeneity regarding:

- Provided services and covered airspaces,
- Systems and tools, working procedures,
- Data collection processes,
- Cost allocation.



Source: NEST. Provided by DFS

ANSP	Covered Airspaces		
	Upper	*Lower*	*Terminal*
Maastricht UAC	X		
Belgocontrol		X	X
ANA Luxembourg			X
Skyguide	X	X	X

Motivation

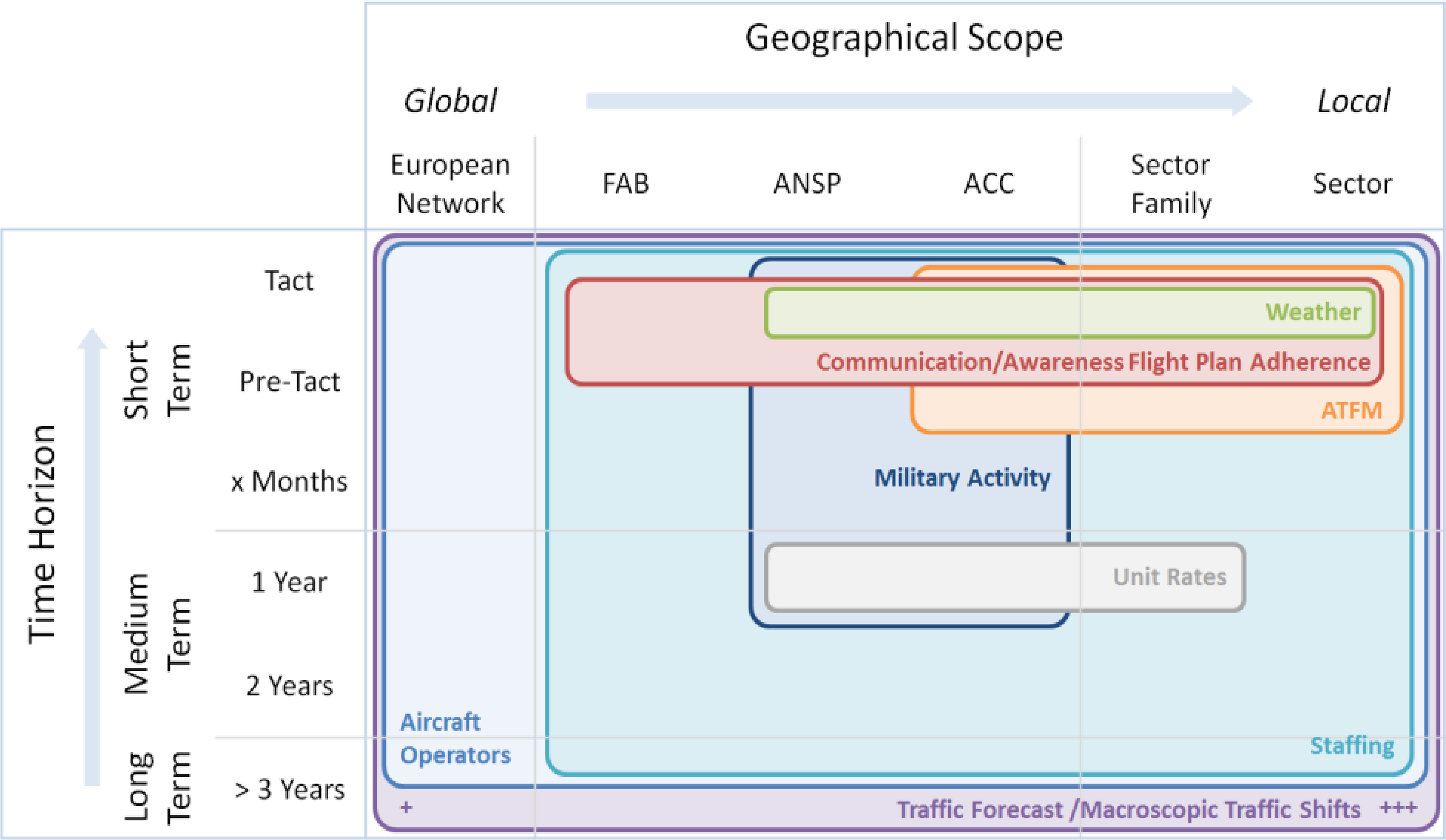
Why to address Traffic volatility?

What is volatility?

- We define volatility as the variability of traffic flows along a specific unit (e.g., ANSP, ACC, or sector) within a given time period (e.g., week).

Initial research questions (selection)?

- How to measure volatility for performance benchmarking?
- Which periodical and operational levels have to be addressed?
- How does volatility influence ANSP performance?
- Has volatility increased over the past years?

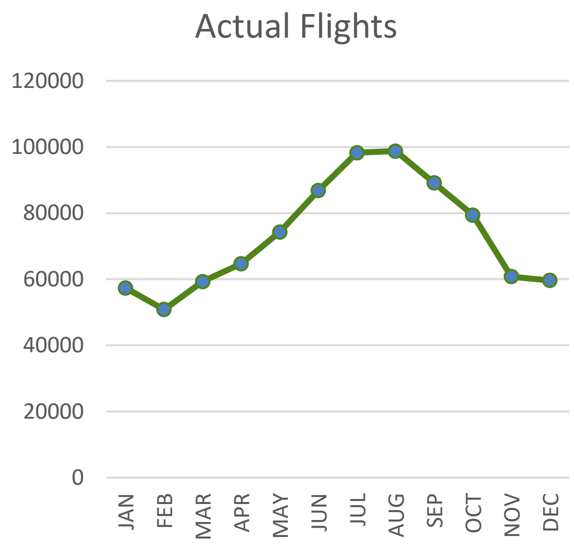


Source: FABEC Volatility Task Force

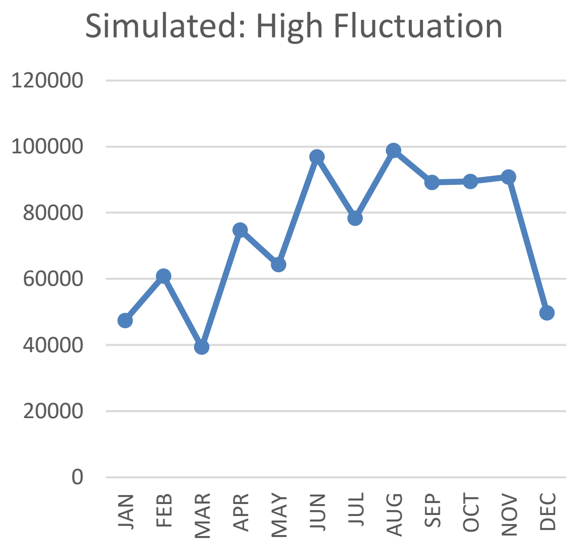
Metrics
Status quo

Proposed Metrics

- FABEC volatility task force suggested a score that sums up unanticipated traffic (for sectors).
- EUROCONTROL introduced a seasonality indicator for performance benchmarking. The score sets the peak load in relation to the average load.



ECTL: 1,35



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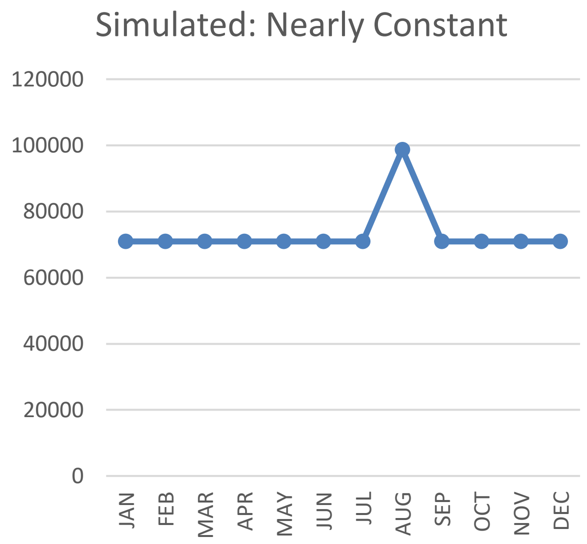

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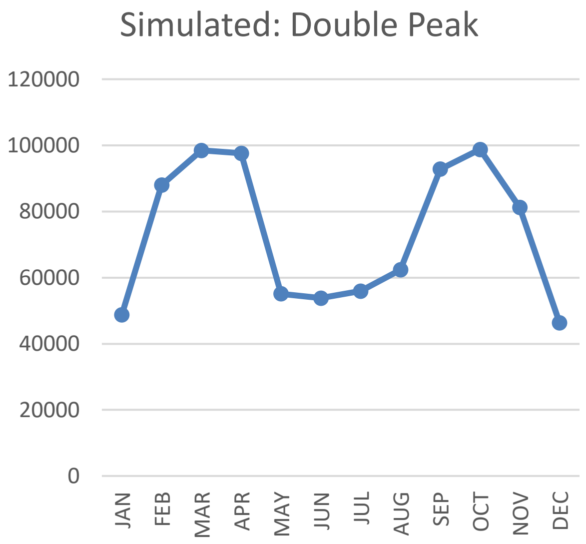


ECTL: 1,35

Metrics

… and Time Horizons

Requirement Engineering

- A metric should reflect changes in demand appropriately (sensitivity regarding traffic scenarios),
- It should consider pan-European heterogeneity,
- It should be applicable on different operational levels.

Some Potential Metrics

$$\sigma = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (R_i - \mu)^2}$$ → scale dependent

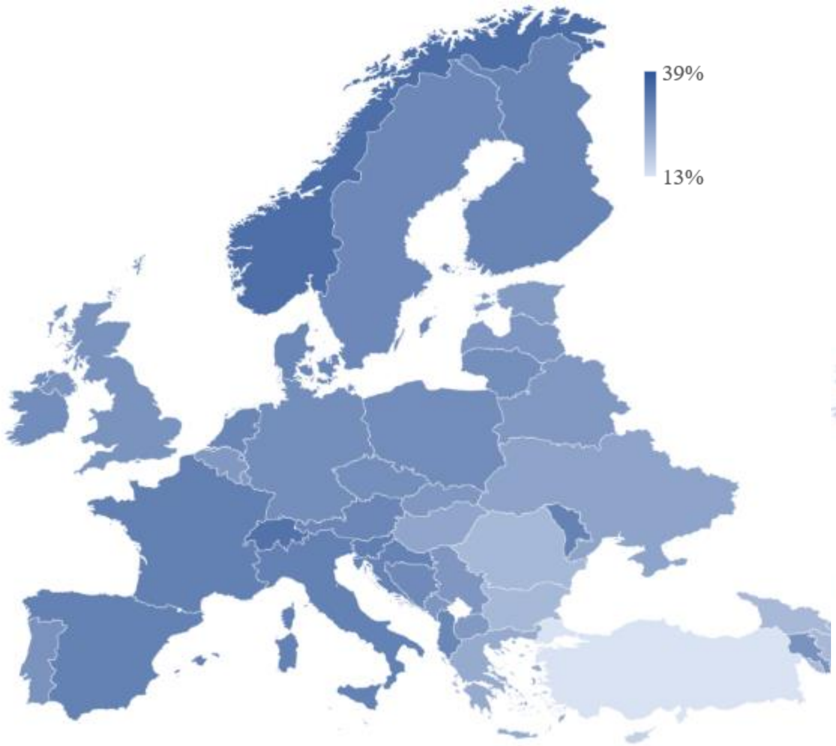
$$GINI = \frac{2 \cdot \sum_{i=1}^{n} i \cdot x_i}{n \cdot \sum_{i=1}^{n} x_i} - \frac{n+1}{n}$$ → scale independent

Temporal Disaggregation

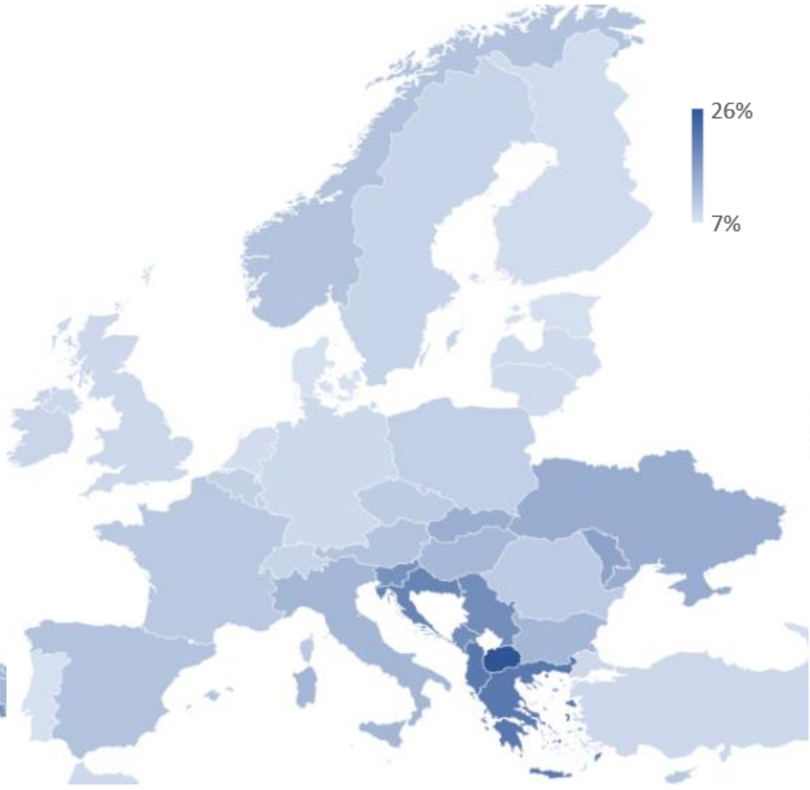
- As shown by FABEC, volatility may act on different time intervals.
- We distinguish three time horizons:
  - The seasonality is considered to be **long-term** volatility.
  - **Medium-term** volatility addresses daily fluctuations within a week. As an example, traffic tends to be lower at weekends.
  - Traffic fluctuations over one day are considered as **short-term** volatility. It is mainly caused by a (relatively) low demand during nighttime.
- Depending on the time interval, different data sources are available, such as NEST data (hourly) or PRU data (daily).

Metrics
Application using GINI coefficient

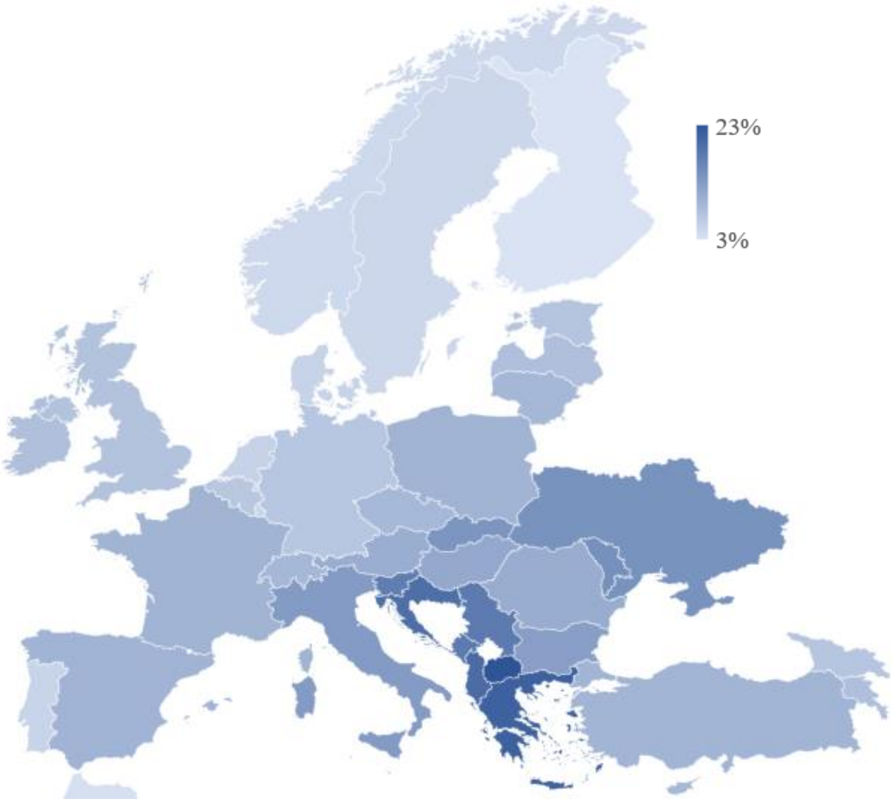
Short-Term



Medium-Term



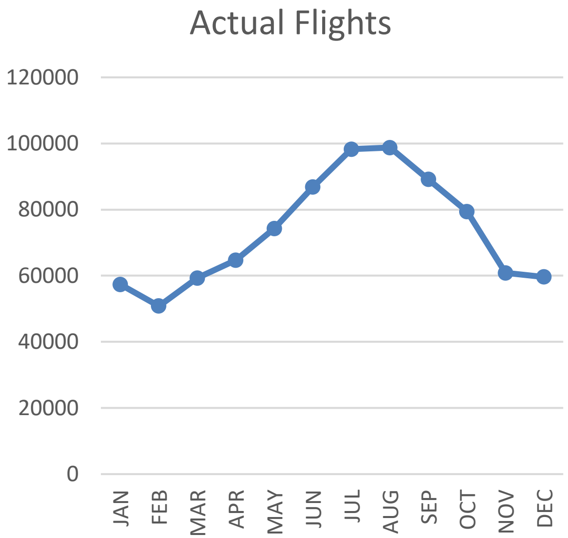
Long-Term



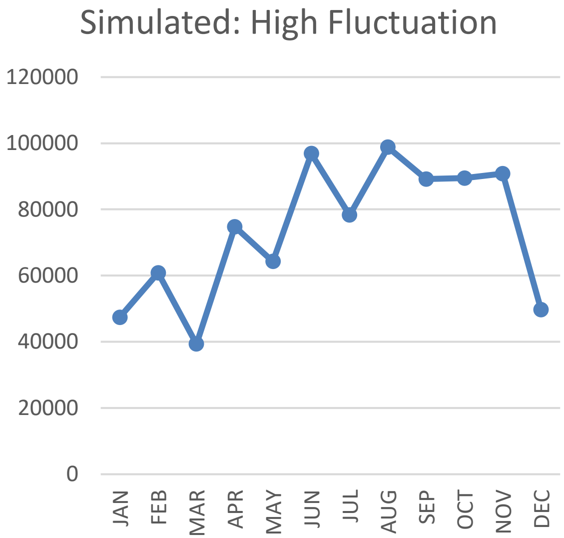
Metrics

Applicability of GINI

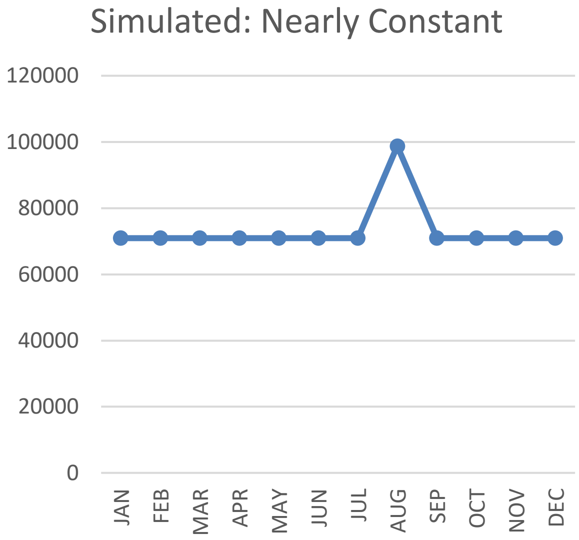
EUROCONTROL score versus GINI coefficient:



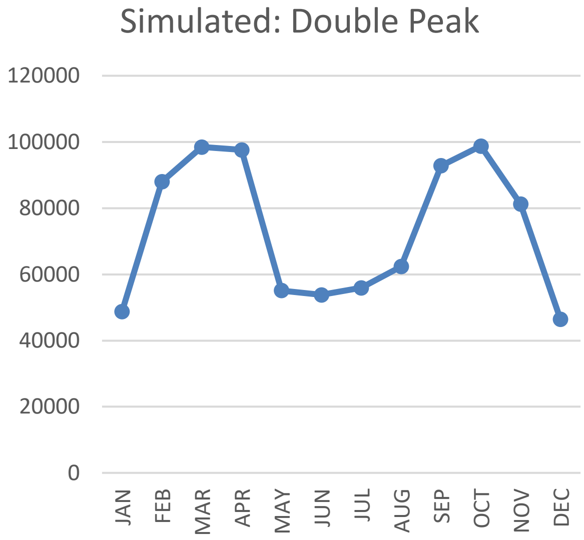
ECTL: 1,35
GINI: 12,4%



ECTL: 1,35
GINI: 15,2%



ECTL: 1,35
GINI: 2,9%



ECTL: 1,35
GINI: 15,5%

Influence on Performance
Model and Method

Goals:

- High volatility is expected to hamper productivity:
  - however, there are multiple further influencing factors,
  - Does each score affect performance equally?
- Method applied: Regression Analysis.
- The model represents an extension of the analyses of a PhD-study. It considers exogenous, partially exogenous, and endogenous factors.
  - The dependent variable is represented by ATCO productivity (see PRU / EUROCONTROL reports).
  - VOL_ST, _MT, and _LT represent the volatility factors.
  - Airspace and traffic characteristics, ownership forms, and socio-economic factors are considered as well
- We calculated both cross-sectional and panel models. Model quality was maximized by variable reduction.

Factor	Metric	Meaning
AIRP	0/1	Airport Ownership
COORD	Nb	Coordination – Number of neighboring airspaces
COSTS	€	Employment costs per ATCO
DELATM	0/1	Delegated ATM
DENSITY	Score	Traffic Density
DOM	%	Share of domestic flights
HI	Score	Horizontal Interactions
JSC	0/1	Joint Stock Company
L_AIRP	Nb	Number of hubs (>200.000 movements p.a.)
MET	0/1	MET Services
NOFAB	0/1	ANSP is no member of a Functional Airspace Block
NONA	%	Share of Non-ATCOs
OCEAN	0/1	Oceanic Airspace
OVER	%	Share of overflights
RES	Nb.	Technology proxy
SI	Score	Speed Interactions
SIZE	Km²	Airspace Size
STATE	0/1	State-Owned
TIME	h	Working time per ATCO
VI	Score	Vertical Interactions
VOL_LT	%	Seasonality
VOL_MT	%	Weekly Volatility
VOL_ST	%	Daily Volatility
WEALTH	€	Wealth of the country, GDP per Capita

Influence on Performance

Results

Results:

- The shown result represents one specification using cross-sectional data.
- In model 1, volatility is expressed by the GINI score, model 2 uses the standard deviation as volatility.
- The results for model 1 are plausible with regard to positive or negative signs of the variables. Further, all variables are statistically significant.
- Using standard deviation (model 2) hardly changes results. The variable DENSITY is now included. All variables are statistically significant, except the constant and DENSITY.
- For neither Model 1 nor Model 2 the VIF test indicates collinearity
- Model quality is high, particularly for model 1.

Variable	Model 1	Model 2
const	-0,36 (0,493)***	-1,317 (0,407)
l_size	0,219 (0,064)***	0,316 (0,066)***
OVER	0,592 (0,141)***	0,559 (0,145)***
VOL_LT	-2,142 (0,621)***	-2,287 (0,674)***
VOL_ST	-1,548 (0,727)*	-0,002 (0,001)**
MAPE	-0,145 (0,082)*	-0,143 (0,083)*
COSTS	0,003 (0,001)***	0,003 (0,001)***
JSC	0,158 (0,058)**	0,143 (0,056)**
DENSITY		0,026 (0,013)
Adj. R^2	**0,79**	**0,79**
Log-Likelihood	**21,20**	**20,51**
AIC	**-24,39**	**-25,01**

Conclusions
What we have learned

1. GINI and Standard Deviation are applicable for benchmarking purposes and improve the currently used EUROCONTROL score.
   a) GINI should be used particularly when comparing different ANSPs or different operational levels.
   b) Standard deviation is to be preferred when analyzing one unit over time.
2. Short- and long-term volatility have a statistically significant impact on productivity/efficiency.
3. The results might be used for an "overall" volatility score. The score might be used as a monitoring value, but also as an indication of the required system resiliency.

$$OVS = u \cdot VOL_{LT} + v \cdot VOL_{ST} = 0.58 \cdot VOL_{LT} + 0.42 \cdot VOL_{ST}$$

4. For most of the ANSPs, volatility increased over the past years (before 2020). Further, extreme values became more often.
5. Volatility increases when disaggregating the operational level (e.g., ACCs, Sector groups).

Thank you

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