## Liquidity Risk and Investor Behavior: Issues, Data and Models

Serge Darolles, Université Paris-Dauphine, joint work with Gaelle Le Fol, Yang Lu and Théo Sun

EIFR, 24 Janvier 2018

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### 3 Data

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- 4 First empirical results
  - Static model
  - Dynamic model
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### 1 Motivation

First example

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### Investment funds and liquidity risk exposure

- Hedge funds perform liquidity transformation and provide different liquidity conditions to investors (mismatch between assets and liabilities)
- But daily mutual funds are also exposed to this liquidity transformation risk, especially when investors are active
- This liquidity transformation risk is related to :
  - the average assets liquidity exposure market liquidity risk
  - the clients' liquidity consumption funding liquidity risk

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### **Previous studies**

- Previous empirical studies have shown that both market and funding liquidity are priced in the cross-section of fund's returns
- Market : SADKA 2006-2010, TEO 2011
- Funding : DUDLEY & NIMALENDRAN 2010 ARAGON & STRAHAN 2012
  - Both: AGARWAL, ARAGON & SHI 2015
  - They mostly use regression evidence using market and funding liquidity indicators on the right-hand side
  - HOMBERT & THESMAR 2014 first paper to endogenize the funding liquidity exposure via constraints on withdrawals

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### Our paper - Understanding investor behavior

- We study the link between the investor behavior and the liquidity risk exposure of an investment fund
- Using a new set of proprietary data on individual investors orders, we can split net flows observed at the fund level
- We use Self-Exciting and Mutual-Exciting processes to model flows' persistence and forecast future flows at the investor level
- We then use these forecasts to predict the future evolution of the fund's asset under management

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### **Research questions**

Question 1 : Do investors adjust their (liquidity) behavior depending on the funds liquidity exposure?

Question 2 : Do we observe lead/lag effects in the behavior of different types of investors ?

Question 3 : Does investor behavior impact the calculation of a Liquidity-adjusted Value-at-Risk ?

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### Related business issues

- Issue 1 : Design new information systems with data at the investor level IT departments
- Issue 2 : Develop portfolio allocation and risk models incorporating time-varying AUM - Research departments
- Issue 3 : New risk metrics to monitor liquidity risk Risk departments

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### 2 First example

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Darolles, Roussellet (2016), *Hedge Fund Portfolio Management with Illiquid Assets*, consider a funds living for 2 periods which has access to two assets :

- **Cash** : zero interest rate, available every period
- Illiquid asset : fixed rate of return ρ<sub>1</sub> + ρ<sub>2</sub>, available at period t = 2 only

The simplified fund balance-sheet is :

Assets	Liabilities
Cash	AUM
Illiquid asset	AUIVI

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Investor behavior				

## Timing

- $t=0~\rightarrow$  The fund chooses a portfolio composition  $\left(\delta,1-\delta\right)$  in cash/illiquid asset
- $t = 1 \rightarrow$  With probability  $\pi$ , a fraction  $\theta$  of AUM is withdrawn by the investors
  - $\label{eq:theta} \theta \sim \mathcal{U}[0,\overline{\theta}], \, \text{where} \; \overline{\theta} \leqslant 1$

  - If θ > δ, the fund has to sell the illiquid asset on a secondary market

 $t = 2 \rightarrow$  The final value of the fund's portfolio is realized

Funding liquidity shock  $\theta$  associated with parameters  $\pi$  and  $\overline{\theta}$ 

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Investor behavior

### Liquidation cost on the secondary market

The illiquid asset has a known return  $\rho_1 + \rho_2$  at period t = 2

•  $\rho_1$  alone would be the friction-less return at period t = 1

#### Market liquidity shock

The realized return of the illiquid asset on the secondary market is equal to  $\rho_1 - T$ , where T is the market liquidity shock

- $T \sim \mathcal{E}(\lambda)$ , where  $\lambda > 0$
- $\blacksquare$   $\lambda$  is an indicator of market liquidity,  $1/\lambda$  is the average rebate on the secondary market

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### When does default arise?

Two situations can arise when a "big"  $\theta$  is observed :

The realized return ρ<sub>1</sub> – T is sufficiently high to cover the discrepancy θ – δ. I sell a proportion γ of the illiquid asset equal to :

$$\gamma(1-\delta)\exp(\rho_1-T) = \theta - \delta \iff \gamma = \frac{\theta - \delta}{1-\delta}\exp(T-\rho_1)$$

If *T* is too high, selling all the illiquid asset is not sufficient to cover θ − δ. The default is triggered whenever :

$$(1-\delta)\exp(\rho_1-T) < \theta - \delta \Longleftrightarrow \gamma > 1$$

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Solving the model

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First empirical results

### Default probability with exogenous cash

- With the assumptions made on liquidity shocks, it is possible to obtain the conditional distribution of γ given a liquidity shock
- The unconditional default probability is a by-product :

Default probability

$$\mathbb{P}(\gamma > 1) = rac{\pi(\overline{ heta} - \delta)^{\lambda + 1}}{\overline{\overline{ heta}}(\lambda + 1)(1 - \delta)^{\lambda}} e^{-\lambda 
ho_1}$$

This probability is decreasing in the market liquidity λ, increasing in the size of the maximal possible funding shock θ and decreasing in the cash amount δ

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### Endogenous cash management

Optimal cash amount (when  $\theta = 1$  - no gate)

$$\delta^*(\lambda,\pi,\rho_1,\rho_2) = \frac{G(\lambda,\rho_1) + H_1(\pi,\rho_1,\rho_2)}{G(\lambda,\rho_1) + H_2(\rho_1,\rho_2)}$$

δ\* is a function of λ (*market liquidity*) through G(·) only
 δ\* is a function of π (*funding liquidity*) through H<sub>1</sub>(·) only

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The main assumption to get this result is :

#### Funding liquidity shock

The value of  $\theta$  is the funding liquidity shock. It is associated with parameters  $\pi$  and  $\overline{\theta}.$ 

# And with a more realistic assumptions on the investor behavior?

Data on individual investor behavior can help to find the good set of assumptions

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#### 3 Data

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- The context A collaborative project between
  - 3 French asset management companies
  - A consultancy firm specialized in clients services
  - An IT firm
  - An academic research team
- The project started two years ago
- The database does not exist yet only non structured data at each AM company level
- The main task is to design a data format and create the database

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Universe				

#### Size

- Today : several hundreds of funds
- Tomorrow : several thousands of funds

#### Limitations

Today : we observe trades within each companies

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Tomorrow : no limitation

### Approaches

- Today : at each funds level
- Tomorrow : at the industry level

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### Descriptive statistics (1/3)

Firm	Fonds	Category	# Shares	Inception	AUM
AM 1			16		4 292 294 936
	Funds 1	Euro Equity Large Cap	3	02/10/1998	329 723 439
	Funds 2	Euro Equity Mid/Small Cap	2	06/09/1991	376 326 122
	Funds 3	Euro Fixed Income	2	03/07/1992	255 141 000
	Funds 4	Euro Fixed Income	3	24/02/1982	375 685 999
	Funds 5	Euro Fixed Income	3	05/02/1990	935 044 376
	Funds 6	Euro Money Market	2	31/12/1985	450 074 000
	Funds 7	Euro Money Market	1	07/07/1995	1 570 300 000
AM 2			19		4 384 532 001
	Funds 8	Euro Equity Large Cap	5	20/11/2001	280 424 002
	Funds 9	Euro Equity Mid/Small Cap	5	11/05/1994	333 368 999
	Funds 10	Euro Fixed Income	5	25/10/2000	354 900 000
	Funds 11	Euro Money Market	4	08/03/2006	3 415 839 000
AM 3			8		2 037 509 155
	Fonds 12	Euro Money Market	2	01/04/2013	1 319 876 994
	Fonds 13	Euro Equity Large Cap	3	09/01/2001	295 271 161
	Fonds 14	Euro Equity Mid/Small Cap	2	14/02/1997	34 287 000
	Fonds 15	Euro Money Market	1	30/11/2001	388 074 000
Total			42		10 714 366 092

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### Descriptive statistics (2/3)

	С		0	E	F	G	н		J	K	L	M	N	0
1	Secteur	Sous-s	secteur	Statut	Client Anonymisé	Quantité	Montant net	Date cours	Devise opé.	Stock	Statut	ISIN	Cours	Sens
2	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 964	-1 500,00	-162 945,00	13/01/15	EUR	0	Provisoire ap	FR00009798	108,63	
3	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 718	6 300,00	684 369,00	09/01/15	EUR	34300	Valorisé	FR00009798	108,63	
4	Family Office	OFIN -	Other	Client	Client OFI 870	9 259,00	1 005 712,58	05/01/15	EUR	9259	Valorisé	FR00009798	108,62	
5	OPCVM Grou	OPCV	M Grou	OPC OFI	Client OFI 802	-189 000,00	-20 525 400,	29/12/14	EUR	0	Valorisé	FR00009798	108,6	
6	Association /	OFIN -	Other	Mandat OFI	Client OFI 834	-4 200,00	-456 162,00	24/12/14	EUR	0	Valorisé	FR00009798	108,61	
7	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 845	-6 400,00	-695 104,00	24/12/14	EUR	0	Valorisé	FR00009798	108,61	
8	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 845	6 400,00	695 104,00	24/12/14	EUR	6400	Valorisé	FR00009798	108,61	
9	Association /				Client OFI 834	4 200,00	456 162,00	24/12/14	EUR	4200	Valorisé	FR00009798	108,61	
10	CIBTP	INSC -	Insura	Client	Client OFI 195	-921	-100 020,60	23/12/14	EUR	6491,9	Valorisé	FR00009798	108,6	
11	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 648	-7 500,00	-814 500,00	23/12/14	EUR	0	Valorisé	FR00009798	108,6	
12	Family Office	OFIN -	Other	Client	Client OFI 870	-18 708,00	-2 031 688,8	23/12/14	EUR	0	Valorisé	FR00009798	108,6	
13	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 648	7 000,00	760 200,00	23/12/14	EUR	7000	Valorisé	FR00009798	108,6	
14		Other	s	OPC OFI	Client OFI 508	6 355,00	690 089,45	22/12/14	EUR	6355	Valorisé	FR00009798	108,59	
15	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 889	1 400,00	152 026,00	22/12/14		3400	Valorisé	FR00009798	108,59	
16	CIBTP		Insura		Client OFI 195	-3 685,00	-400 080,45	19/12/14		7412,9	Valorisé	FR00009798		
17	OPCVM Grou	OPCV	M Grou	Client	Client OFI 372	-19 822,88	-2 151 178,5			-19822,877	Valorisé	FR00009798		
18	Mutuelle d'A				Client OFI 111	-10 330,00	-1 121 011,6			0	Valorisé	FR00009798		
19	OPCVM Grou	OPCV	M Grou	Client	Client OFI 372	19 822,88	2 151 178,56	17/12/14	EUR	0	Valorisé	FR00009798	108,52	
20	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 718	-10 000,00	-1 085 100,0	16/12/14	EUR	28000	Valorisé	FR00009798	108,51	
21	IRP	PFND	- Pensi	Client	Client OFI 963	-92 378,75	-10 026 789,	15/12/14	EUR	0	Valorisé	FR00009798	108,54	
22	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 692	10 000,00	1 085 400,00	15/12/14	EUR	19250	Valorisé	FR00009798		
23	Mutuelle d'A				Client OFI 964	-1 000,00	-108 620,00	08/12/14			Valorisé	FR00009798		
24	Mutuelle d'A				Client OFI 490	4 600,00	499 652,00	08/12/14			Valorisé	FR00009798		
25	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 648	-2 500,00	-271 500,00	04/12/14	EUR	7500	Valorisé	FR00009798	108,6	
26	CIBTP		Insura		Client OFI 283	42 000,00	4 561 200,00	04/12/14	EUR	292200	Valorisé	FR00009798	108,6	
27	Mutuelle d'A				Client OFI 964	-1 000,00	-108 610,00	26/11/14		7000	Valorisé	FR00009798		
28	Plateforme				Client OFI 54	-1		25/11/14			Valorisé	FR00009798		
29	Mutuelle d'A				Client OFI 964	-1 000,00	-108 610,00	25/11/14			Valorisé	FR00009798		
30	CIBTP		Insura		Client OFI 276	9 207,26	1 000 000,00			9207,2553		FR00009798		
31	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 673	11 000,00	1 194 710,00	25/11/14	EUR	11000	Valorisé	FR00009798	108,61	
32	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 501	-21 850,00	-2 372 473,0			0	Valorisé	FR00009798		
33	Entreprises				Client OFI 444	73 500,00	7 982 100,00				Valorisé	FR00009798		
34	Compagnie o				Client OFI 570	36 822,00	3 998 869,20				Valorisé	FR00009798		
35	Mutuelle d'A	INSC -	Insura	Mandat OFI	Client OFI 718	-5 000,00	-543 050,00	17/11/14	EUR	38000	Valorisé	FR00009798	108,61	

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### Descriptive statistics (3/3)

Funds	Period	# Days		Number			Freq (in days)	
			Inflows	Outflows	trades	Inflows	Outflows	trades
AM 1			522 015	283 034	805 049			
Funds 1	2013-14	497	174 903	22 134	197 037	351,91	44,53	396,44
Funds 2	2013-14	497	144 992	20 880	165 872	297,73	42,01	399,74
Funds 3	2013-14	497	18 942	6 436	25 378	38,11	12,95	51,06
Funds 4	2013-14	497	3 709	5 983	9 692	7,46	12,04	19,50
Funds 5	2013-14	497	5 671	7 323	12 994	11,41	14,73	26,14
Funds 6	2013-14	497	36 779	54 044	90 823	74	108,74	182,74
Funds 7	2013-14	497	137 019	166 234	303 253	275,69	334,47	610,37
AM 2			52 773	68 955	121 728			
Fonds 8	2010-14	1252	7 005	6 354	13 359	5,60	10,67	16,27
Fonds 9	2010-14	1252	5 663	4037	9 700	4,52	7,75	12,27
Fonds 10	2010-14	1252	1 399	6 952	8 351	1,12	6,67	7,79
Fonds 11	2010-14	1252	38 706	51 612	90 318	30,92	72,14	103,05
AM 3			4 119	5 299	9 418			
Fonds 12	2013-14	493	210	312	522	0,43	0,63	1,06
Fonds 13	2010-14	1 249	1 468	1 400	2 868	1,18	1,12	2,3
Fonds 14	2010-14	1 1 1 5	1 877	3 023	4 900	1,68	2,71	4,39
Fonds 15	2010-14	1 233	564	564	1 128	0,46	0,46	0,91
Total			578 907	357 288	936 195			

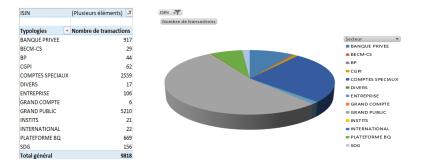
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Conclusion and next developments

#### Universe

### Flows by Investors type



- What is the best classification?
- Do we observe a different behavior by type ?

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Examples				

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### 1. At the monthly inflow and outflow level

#### We can disentangle in- and outflows from net flows

Secteur	(Tous)			
Sous-secteur	(Tous)			
ISIN	(Tous)			
Année/Flux	Flow			
Mois	J OutFlow		InFlow	NetFlow
8 2014		-328700847,3	513425116,7	184724269,
1		-24726353,72	144556851,8	119830498,1
2		-5630282,42	18032710,1	12402427,68
3		-80736321,86	67354412,57	-13381909,25
4		-15170602,45	34321809,48	19151207,03
5		-15460185,51	21770528,88	6310343,37
6		-37769565,19	16589432,99	-21180132,3
7		-26184373,84	56611316,3	30426942,48
8		-9668516,67	21977191,57	12308674,5
9		-20838975,99	45134827,69	24295851,3
10		-40785431,35	19138840,92	-21646590,43
11		-7534171,5	29261331,44	21727159,94
12		-44196066,84	38675862,93	-5520203,91
NetFlow		-328700847,3	513425116,7	184724269,3

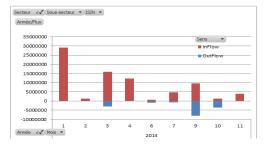


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### 2. For an investors type

#### All "Insurance" clients in 2014

Secteur	Compagnie d'Assura	nce 🗷		
Sous-secteur	(Tous)			
ISIN	(Tous)	¥		
Année/Flux	Flow			
Mois 🦪	OutFlow		InFlow	NetFlow
82014	-16	334097	78647581,66	62313484,66
1			29129300	29129300
2			1291780	1291780
3	-2	907840	15917768,5	13009928,5
4	-	215620	12160371,46	11944751,46
6	4	898226	757050	-141176
7	-	800976	4675764,5	3874788,5
9	-8	006562	9523068	1516506
10	-3	504873	1193610	-2311263
11			3998869,2	3998869,2
NetFlow	-16	334097	78647581,66	62313484,66



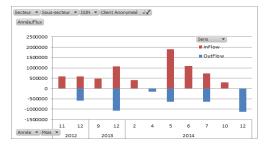
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### 3. For a single investor

#### Client 111 history on the last 3 years

Secteur	(Tous)	Ŧ		
Sous-secteur	(Tous)	¥		
ISIN	(Tous)	-		
Client Anonymi	isé Client OFI 111	Τ.		
Année/Flux	Flow	-		
Mois	<ul> <li>OutFlow</li> </ul>		InFlow	NetFlow
B 2012				
11			590072	590072
12	-592	144	592144	0
≅ 2013				
9			470228	470228
12	-1073	300	1073800	0
B 2014				
2			397898	397898
4	-14771	3,4		-147713,4
5	-647	380	1905280	1257400
6			1082100	1082100
7	-6494	140	722100	72660
10			304014	304014
12	-112101	1,6		-1121011,6
NetFlow	-4231	989	7137636	2905647



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Motivation	First example	<b>Data</b> 000000 000	First empirical results	Conclusion and next developments

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### 4 First empirical results

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Static model				

We start with a simple (static) model to fit the data :

The natural choice is a Poisson distribution

We extend this first model step by step :

- by adding parameters to capture observed stylized facts
- by evaluating the model quality with standard criteria (Mean Square Error, AIC ...)

For presentation purpose, we first use only one (very liquid) funds to compare the different specifications. Only the last model is estimated on 4 funds with different liquidity levels

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#### Static model

1D Homogenous Poisson Model (with over-dispersion)

$$N_t = \mathscr{P}(\lambda F_t) = \mathbb{P}(\lambda, \gamma)$$

- *N<sub>t</sub>* : aggregated trades (inflows and outflows)
- $\lambda$  : intensity of Poisson distribution
- *F<sub>t</sub>* > 0 with *E*(*F<sub>t</sub>*) = 1 : latent factor introduced to create over-dispersion negative binomial distribution (parameter γ)

Model	λ	γ	
1D (H)	54.46***	21.45***	

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With our dataset, we can then treat separately inflows and outflows in a two-dimensional model

#### 2D Homogenous Poisson Model

$$egin{aligned} & \mathcal{N}_t^{\textit{in}} = \mathbb{P}(\lambda^{\textit{in}},\gamma^{\textit{in}}) \ & \mathcal{N}_t^{out} = \mathbb{P}(\lambda^{out},\gamma^{out}) \end{aligned}$$

Model	$\lambda^{in}$	$\lambda^{out}$	γ <sup>in</sup>	γ <sup>out</sup>
2D (H)	25.13***	29.32***	17.48***	22.61***

But very bad predictors ....

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developments



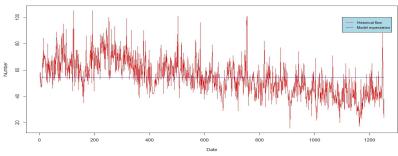
First example

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#### Static model

### Model prediction : 2D (H) - inflows

We compute the 1-day predicted value (*blue line*) and compare it to the realized value (*red line*)



Historical flows vs model expectation

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Dynamic model

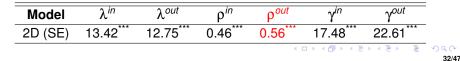
We observe both persistence and clustering effects on flow series. Only a dynamic model can capture these effects

#### 2D Self-Exciting Model

$$\lambda_t^{in} = \lambda_0^{in} + 
ho^{in} N_t^{in}$$
  
 $\lambda_t^{out} = \lambda_0^{out} + 
ho^{out} N_t^{out}$ 

 $\lambda_0^{in/out}$  : a constant term (base intensity)

 ρ<sup>in/out</sup>: the correlation term (the previous flow will "update" the next intensity)



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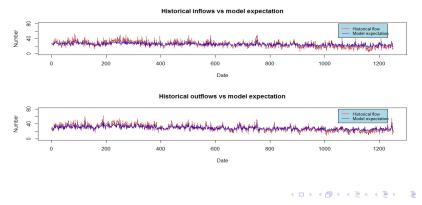
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Dynamic model

## Model prediction : 2D (SE)

We compute the 1-day predicted value (*blue line*) and compare it to the realized value (*red line*)



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Dynamic model

The persistence effects of flows can be completed by adding cross effects between inflows and outflows

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#### 2D Mutual-Exciting Model

$$\begin{split} \lambda_t^{in} &= \lambda_0^{in} + \rho^{in-in} N_t^{in} + \rho^{in-out} N_t^{in} \\ \lambda_t^{out} &= \lambda_0^{out} + \rho^{out-in} N_t^{in} + \rho^{out-out} N_t^{out} \end{split}$$

- ρ... : The impact of previous flows to next intensity
- e.g. p<sup>in-out</sup> : correlation of the inflow intensity to the previous outflow
- e.g.  $\rho^{out-out}$  : correlation of the outflow intensity to the previous outflow
- Other parameters in the model are as same as previous model

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Dynamic model

### What "Self/Mutual Exciting" means?

### "Self Exciting"

	Previous Inflow	Previous Outflow
Inflow	reputation	
Outflow		financial runs/ panic

#### "Mutual Exciting"

	Previous Inflow	Previous Outflow
Inflow	reputation	commercial ability
Outflow	smart money	financial runs/ panic

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### **Empirical results**

#### **TABLE : Estimators**

Model	λ <sup>in</sup>	$\lambda^{out}$	In-In	In-Out	Out-In	Out-Out	γ <sup>in</sup>	$\gamma^{out}$
1D (H)	54.46***						21.45***	
2D (H)	25.13***	29.32***						22.61***
2D (SE)	13.42***		0.46***			0.56***	17.49***	22.62***
2D (ME)	8.15***	10.84***	0.32***	0.30***	0.19***	0.46***	35.56***	44.94***

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### **Empirical results**

#### TABLE : Model quality

Model	Param.	MSE-In	MSE-Out	MSE-All	AIC
1D (Homo)	2			239903.1	
2D (Homo)	4	74821.25	84638.42	159459.7	-315870.4
2D (SE)	6	60588.69	59129.57	119718.3	-316328.2
2D (ME)	8	55940.79	57183.28	113124.1	-316478.2

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Dynamic model

## 4 funds (different categories)

TABLE : Model estimation

Category	λ <sup>in</sup>	λ <sup>out</sup>	In-In	In-Out	Out-In	Out-Out	γ <sup>in</sup>	$\gamma^{out}$
MoneyMarket	8.1***	10.1***	0.32***	0.30***	0.19	0.46***	35.5***	44.9***
EqtyLarCap							35.9***	68.8***
EqtySmallCap	0.5***	1.1***	0.52***	0.06**	0.16***	0.19***	2.5***	4.4***
FixedIncome	0.4***	0.4***	0.10*	0.00	0.00	0.02	0.5***	0.7***

Research question 1 : **YES** - Investors adjust their (liquidity) behavior depending on the funds liquidity exposure

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First example

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Contagion model

### Contagion : dependence between clients types

Objectives :

- **1** Empirical evidences of contagion between types
- Analyze the risk when the liability composition is time varying
- 2 sectors :
  - Insurance (AS) & "Social protection group" (PS)
  - Linked activities
  - Significant flows (AS 13 537 & PS 11 031)

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Contagion model				

### 2 x 2D (ME) model

#### We first estimate two 2D (ME) model for comparison purpose

#### TABLE : 2D (ME) Model estimation for two types

Model	$\lambda^{in}$	$\lambda^{out}$	In-In	In-Out	Out-In	Out-Out	γ <sup>in</sup>	γ <sup>out</sup>
AS-2D (ME)	3.25***	4.26***	0.19***	0.08 <sup>*</sup>	0.05*	0.25***	7.76***	36.63***
PS-2D (ME)	2.86***	2.54***	0.31***	0.08**	0.08**	0.29***	6.47***	4.93***

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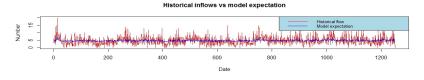
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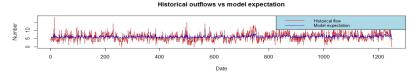
Conclusion and next developments

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#### **Contagion model**

## Model quality : 2D (ME) for AS





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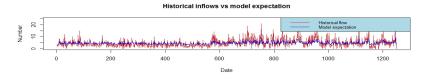
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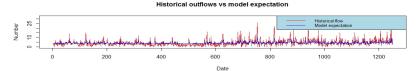
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Conclusion and next developments

**Contagion model** 

## Model quality : 2D (ME) for PS







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#### **First empirical results**

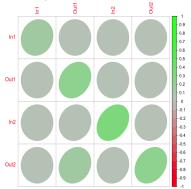
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**Contagion model** 

### 4D model (Contagion)

#### Contagion matrix



#### Estimators

		-			
	Estimate	Std. Error	z value	Pr(z)	
Base_in1	3.931456	0.272512	14.4267	< 2.2e-16	
Base_out1	4.115734	0.291452	14.1215	< 2.2e-16	
Base_in2	2.275925	0.291452 0.267991	8.4926	< 2.2e-16	
Base_out2	1.632884	0.260640 0.029549	6.2649	3.730e-10	
In1_In1	0.116882	0.029549	3.9555	7.638e-05	
In1_Out1	0.001000	0.031909 0.025437	0.0313	0.974999	
In1_In2	0.034625	0.025437	1.3612	0.173461	
In1_Out2	0.019175	0.025261	0.7591	0.447799	
Out1_In1	0.032231	0.025261 0.029968	1.0755	0.282154	
Out1_Out1	0.227773	0.034969 0.027638	6.5136	7.338e-11	
Out1_In2	0.018554	0.027638	0.6713	0.502014	
0 + 1 + 0 + 2	A A07700	A A20A15	2 1162	A AA1000	
In2_In1	0.030685	0.028015 0.027705 0.032438 0.029389 0.028191	1.1076	0.268046	
In2_Out1	0.091277	0.032438	2.8139	0.004895	
In2_In2	0.300877	0.029389	10.2377	< 2.2e-16	
In2_Out2	0.066998	0.028191	2.3766	0.017473	
Out2 In1	0.017244	0.027520	0.6266	0.530915	
Out2_Out1	0.161549	0.033942 0.027268 0.032503	4.7595	1.940e-06	
Out2_In2	0.074917	0.027268	2.7475	0.006005	
Out2_Out2	0.267678	0.032503	8.2356	< 2.2e-16	
Gamma_In1	10.641801		6.7262	1.741e-11	
Gamma_Out1	22.707555	2.417837	9.3917	< 2.2e-16	
Gamma_In2	7.521537	0.858245	8.7639	< 2.2e-16	
Gamma_Out2	5.136202	0.450970	11.3892	< 2.2e-16	
Signif. co	des: 0 '*	**' 0.001 '×	<b>**'</b> 0.01	<b>'*' 0.05</b>	'.' 0.1 ' ' 1
-2 log L: ·	-30979.89				

Research question 2 : YES - we observe lead/lag effects between different types of investors

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Conclusion and next developments

**Contagion model** 

### Empirical results - 2 types

#### TABLE : Model quality

Model	Ν	MSE-In	MSE-Out	MSE-All
AS 2D (ME)	8	9297.692	7031.586	16329.28
AS 4D (ME)	12	9291.72	7005.21	16296.93
PS 2D (ME)	8	10867.42	11407.5	22274.92
PS 4D (ME)	12	10819.93	11168.1	21988.03

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### 5 Conclusion and next developments

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### **Research questions**

- Question 1 : YES Investors adjust their (liquidity) behavior depending on the funds liquidity exposure
- Question 2 : YES we observe lead/lag effects between different types of investors

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Question 3 : YES - Investor behavior impacts the calculation of a Liquidity-adjusted Value-at-Risk

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- First steps in the modeling of individual investor behavior
- Inflows and outflows must be considered separately
- Clients types are also important to consider
- Measure contagion at the industry level (and not just at the funds level)

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Start to to do big data things !