How liquid is the CDS market?

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What do we do in this paper?

- Take a microscopic view of CDS markets, by looking at intra-daily data from a major interdealer broker
- Look at transaction costs and trade frequency for CDS's

→ We find both of these to be similar as their counterparts for corporate bonds, as reported in the literature

- Our data allows us to document the intra-daily distribution of trade and quote arrivals.

→ Quotes peak before trades

→ Trades do not pick up at the end of the day

What do we do in this paper?, cont'd

- Set-up an econometric model linking the observations to an unobserved efficient CDS premia that follows a random walk with fat-tailed innovations
  - Allow for stochastic transaction costs and outliers
  - Allow for intra-daily patterns in volatility and transaction costs
- Solve the resulting nonlinear filtering problem using particle filtering and estimate the model using the Monte Carlo EM algorithm

→ Find a J-shape pattern during the day both for volatility and transaction costs.

→ Transaction costs seem to be inversely related to trade intensity

Connection to existing literature

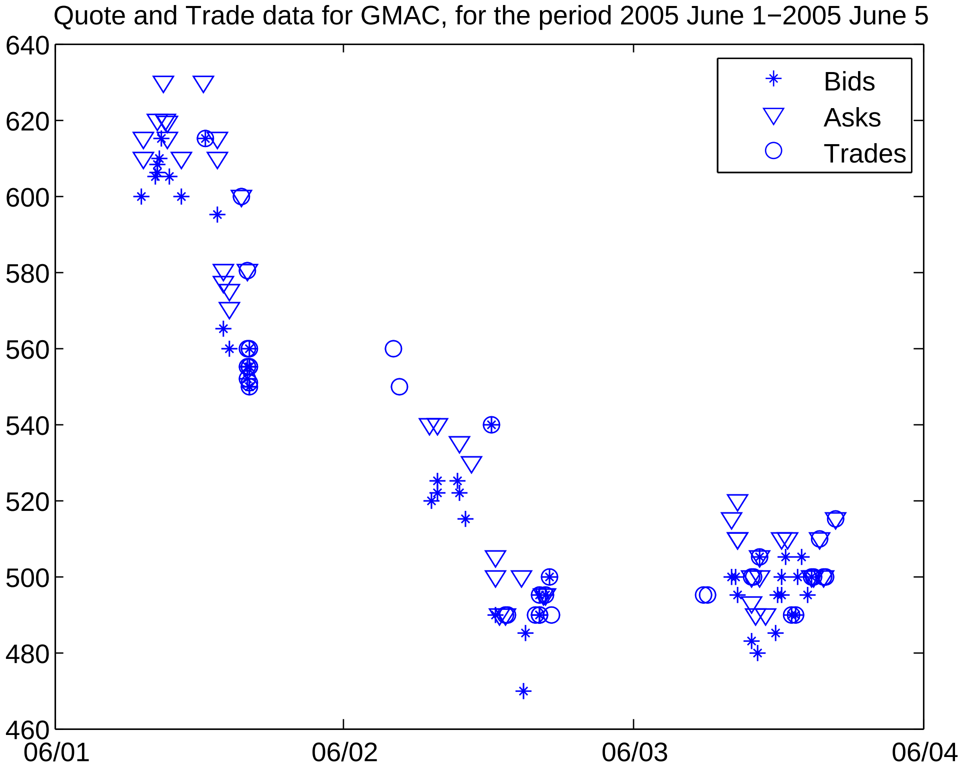
- There is a body of literature looking at CDS prices using daily data
  - CDS prices seem to be relatively efficient informationally: Blanco,Brennan and Marsh (2005), Hull,Predescu and White (2004)
  - There seems to be some evidence for the presence of insider trading: Acharya and Johnson (2007)
  - CDS spreads seem to contain an element that is compensation for illiquidity: Tang and Yan (2006)
- Microstructure literature on motives for participating on IDB's: Asymmetric Info and/or Inventory Motives? Bjonnes and Rime (2005), Reiss and Werner (1998,2004)

Outline

1. Data
2. Econometric Model and Estimation Method
3. Estimation Results

- Intra-daily CDS quote and trade data from GFI for 2004-2006 on Ford,GMAC,Sears,France Telecom
- GFI is one of the major IDB's for CDS's (60% self-reported market share)
- IDB's 34% of trades in 2004 (BBA)
- Anonymous platform

- Data timestamped down to a minute
- CDS premia in bp, on 5-year maturity
- Tick size is 1 bp most of the time, very rarely 0.5 bp
- No trade direction indicator, no size
- Quote heterogeneity, Outliers, Irregularly spaced observations



Quote and Trade data for GMAC, for the period 2005 June 1−2005 June 5
640
620
600
580
560
540
520
500
480
460
06/01
06/02
06/03
06/04
Bids
Asks
Trades

Table 2 Panel A

Descriptive statistics from the raw dataset

Data is between 2004-2006

	Entity			
	Ford	**GMAC**	**Sears Acceptance**	**France Telecom**
Daily Average # bid	*5,81*	*6,65*	*2,49*	*4,32*
N bid	*4265*	*4936*	*1356*	*3078*
Average bid	332	344	106,23	41,27
Daily Average # ask	*5,12*	*6,18*	*2,07*	*4,24*
N ask	*3759*	*4589*	*1127*	*3017*
Average ask	341	352	114,65	42,78
Daily Average # trade	*2,57*	*4,46*	*0,78*	*1,42*
N trade	*1891*	*3313*	*425*	*997*
Average trade price	367	393	113,46	42,38

Trade Frequency

- Comparison: Average number of daily trades for corporate bonds
  - US: Edwards,Nimalendran and Piwowar (2006), 3.7; Edwards,Harris and Piwowar (2007), 1.9
  - Europe: Biais and Declerck (2007), 4;
- The number of trades is similar for CDS than for corporate bonds. (however typical trade size for CDS is much bigger, around 5-10 million according to brokers)

Measuring transaction costs

- To get a rough feeling on the magnitude of transaction costs, use quoted bid-ask spreads.
- After a roundtrip, a trader is left with a cash flow stream that is paid up to the maturity of the CDS (5 year) or the default of the underlying.
- The roundtrip cost is the present value of this cash flow stream
- E.g. if b/a spread is 10 bp, 5 year maturity, riskfree rate is 5%, recovery rate is 40 %, spread is 400 bp, the roundtrip cost will be around 37 bp.

Table 2 Panel B

Results from the dataset used for estimation

	Entity			
	Ford	**France Telecom**	**GMAC**	**Sears Acceptance**
N bid	*2611*	*1640*	*2991*	*714*
Average bid	335	40,49	351,45	107,34
N ask	*2149*	*1583*	*2681*	*509*
Average ask	343	40,95	359,25	115,59
N bid/ask pair	*1420*	*1276*	*1656*	*568*
Average midpoint(*)	331	43,61	331,185	109,42
Average b/a spread(*)	10,08	2,87	9,7	9,26
Risky Annuity Factor(**)	3,84	4,32	3,84	4,20
Average cost of a round-trip	38,68	12,39	37,22	38,89
Minimum tick, K	1	0,5	0,5	1

Data is between 2004-2006

At most 1 bid and ask observation has been kept for an identical time stamp (this is per minute)

Only observations where the ask is higher than the bid has been kept

(*) These statistics have been computed using the observation with both a bid and an ask

(**) We computed the cost of the 5 year risky annuity for the 5-year

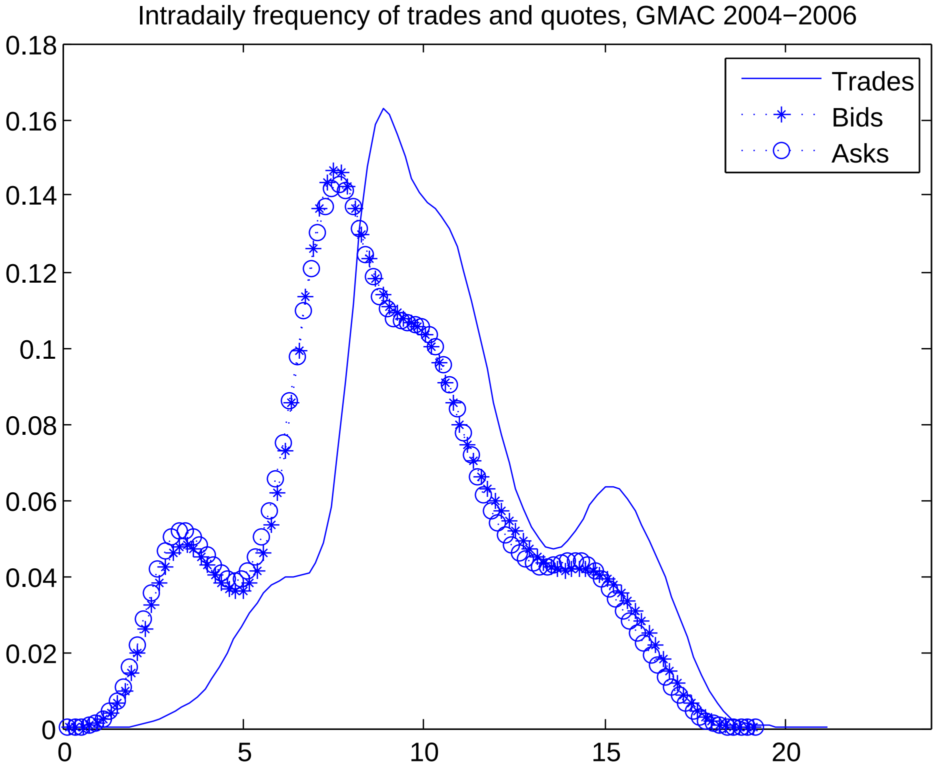
CDS using a 5% interest rate 40% recovery value

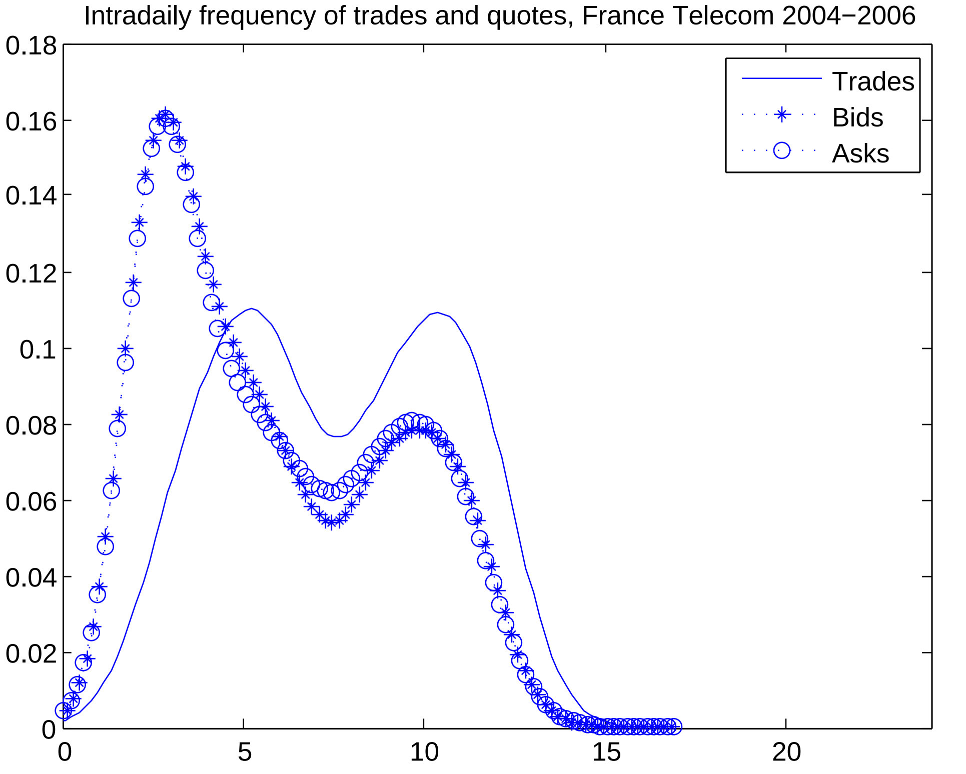
Transaction Costs

- Comparison: Transaction costs for corporate bonds
  - US: Edwards,Harris and Piwowar (2007), effective cost $\sim$ 20 bp
  - Europe: Biais and Declerck (2007), average quoted spread $\sim$ 30 bp
- So trading costs in CDS markets are actually not lower than in corporate bond markets!
- Microstructure phenomena are likely to be important in CDS markets
- Beware when interpreting CDS premia as a pure measure of credit risk!

Why do dealers participate in an anonymous IDB?

- To manage their inventory positions → Trading activity and the number of trades should pick up at the end of the day
- To trade on private information (price discovery)
  - → High level of transaction costs and volatility at the beginning of the day


Intradaily frequency of trades and quotes, GMAC 2004−2006
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.18
0
5
10
15
20
Trades
Bids
Asks


Intradaily frequency of trades and quotes, France Telecom 2004−2006
Trades
Bids
Asks
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
5
10
15
20

- Important stylized facts from the histograms
  - Quote arrival precedes trade arrival within the day (price discovery and/or competition?)
  - Number of trades does not spike up at the end of the day
  - Some American/European cross-activity, but no activity in Asian business hours
- For further analysis, set-up and estimate a model on quote data that allows intra-daily patterns in transaction costs and volatility
- In any minute keep last bid and/or ask observation
- Discard all observations where $Ask \leq Bid$.

Outline

Efficient Price Model

- Irregular observation times at $\tau_i, i = 0, ..., T$, $\mathcal{D}_i$ denotes info up to τ_i
- We either have a bid, B_{τ_i}, an ask A_{τ_i} or both
- Assume that the efficient log spread $m_{\tau_i}(= log(M_{\tau_i}))$ follows the following process

$$m_{\tau_i} = \mu_m \Delta\tau_i + (1 - \rho\Delta\tau_i)m_{\tau_{i-1}} + \sigma_{f(\tau_{i-1},\tau_i)}\sqrt{\Delta\tau_i}\,(u_i + N_i Z_i)$$

where u_i is standard normal, N_i is a Bernoulli, with parameter λ and Z_i is normal with mean μ_J and variance Z_J

Transaction costs

- Dealers are subject to stochastic costs of market making

$$c_{i,A} \sim N(\mu_{\tau_i}, \sigma^2_{c,A}) \text{ constrained to } c_{i,A} > 0$$
$$c_{i,B} \sim N(\mu_{\tau_i}, \sigma^2_{c,B}) \text{ constrained to } c_{i,B} > 0$$

- In the absence of tick restrictions, a market maker would bid

$$B_{\tau_i} = M_{\tau_i} - C_{i,B} = e^{m_{\tau_i} - (c_{i,B} + q_i^A \varepsilon_i^A)}$$

and offer(ask) $A_{\tau_i} = M_{\tau_i} + C_{i,A} = e^{m_{\tau_i} + c_{i,A} + q_i^B \varepsilon_i^B}$

Outliers and discretization

- $q_i^A \varepsilon_i^A$ and $q_i^B \varepsilon_i^B$ represent data errors
- If the tick size is K, the discrete bid and ask prices are given by

$$
\begin{aligned}
B_{\tau_i} &= Floor\left(e^{m_{\tau_i}-(c_{i,B}+q_i^B \varepsilon_i^B)}, K\right) \\
A_{\tau_i} &= Ceiling\left(e^{m_{\tau_i}+c_{i,A}+q_i^A \varepsilon_i^A}, K\right)
\end{aligned}
$$

Intradaily pattern in volatility and transaction costs

- The volatility, $\sigma_{f(\tau_{i-1},\tau_i)}$ and the parameter driving the mean of the transaction costs μ_{τ_i} is allowed to change within the day.
- We parameterize both as a step function within the day
- The partition for US firms (New York time) is

$$\begin{pmatrix} 5.30 & 7.30 & 9.30 & 14.30 & 16.30 \end{pmatrix}$$

- The partition for France Telecom (New York time) is

$$\begin{pmatrix} 0.30 & 2.30 & 4.30 & 7.30 & 9.30 & 14.30 & 16.30 \end{pmatrix}$$

Estimation

- This is a nonlinear and nongaussian state space system
- Use particle filtering to filter the efficient CDS premia given the noisy bid and ask observations.
- Use the Monte Carlo EM algorithm to get the maximum likelihood parameter estimates

Theoretical filtering recursion

$$
\begin{aligned}
& f(a_{\tau_i}, m_{\tau_i}, m_{\tau_{i-1}}, N_i, q_i^A, c_i^A \mid \mathcal{D}_i, c_i^A > 0) \\
\propto \quad & f(c_i^A \mid a_{\tau_i}, m_{\tau_i}, q_i^A, c_i^A > 0) p(c_i^A > 0 \mid a_{\tau_i}, m_{\tau_i}, q_i^A) \\
\times \quad & f(m_{\tau_i} \mid a_{\tau_i}, m_{\tau_{i-1}}, N_i, q_i^A) f(a_{\tau_i} \mid A_{\tau_i}, m_{\tau_{i-1}}, N_i, q_i^A) \\
\times \quad & f(m_{\tau_{i-1}}, N_i, q_i^A, \mid \mathcal{D}_i) \\
\propto \quad & f(c_i^A \mid a_{\tau_i}, m_{\tau_i}, q_i^A, c_i^A > 0) \\
\times \quad & p(c_i^A > 0 \mid a_{\tau_i}, m_{\tau_i}, q_i^A) \\
\times \quad & f(m_{\tau_i} \mid a_{\tau_i}, m_{\tau_{i-1}}, N_i, q_i^A) f(a_{\tau_i} \mid A_{\tau_i}, m_{\tau_{i-1}}, N_i, q_i^A) \\
\times \quad & p(A_{\tau_i} \mid m_{\tau_{i-1}}, N_i, q_i^A) p(N_i) p(q_i^A) f(m_{\tau_{i-1}} \mid \mathcal{D}_{i-1})
\end{aligned}
$$

Particle Filter

Assume that we have M particles, $m_{\tau_{i-1}}^{(m)}$ representing $f(m_{\tau_{i-1}} \mid \mathcal{D}_{i-1})$. Then our localized particle filter with M particles consists of the following steps:

Particle Filter, Step 1

- Enlarge the state-space by the jumps in the system by sampling from N_i and q_i^A, using stratified sampling (to make sure that we have jumps in the sample).
- To arrive at an empirical representation of $f(m_{\tau_{i-1}}, \Delta N_i, q_i^A, \mid \mathcal{D}_i)$ attach to each of the particles weights

$$w_{i,1}^{(m)} = \frac{p(A_{\tau_i} \mid m_{\tau_{i-1}}^{(m)}, N_i^{(m)}, (q_i^A)^{(m)}) p(N_i^{(m)}) p((q_i^A)^{(m)})}{g_1(N_i^{(m)}) g_2((q_i^A)^{(m)})}$$

Particle Filter, Step 2

- Sample from the truncated normal density $f(a_{\tau_i} \mid A_{\tau_i}, m^{(m)}_{\tau_{i-1}|i}, N^{(m)}_i, (q^A_i)^{(m)})$ to generate the particle $(a^{(m)}_{\tau_i}, m^{(m)}_{\tau_{i-1}|i}, N^{(m)}_i, (q^A_i)^{(m)})$.

Particle Filter, Step 3

- Using conditional normality sample from

$$m_{\tau_i}^{(m)} \sim f(m_{\tau_i} \mid a_{\tau_i}^{(m)}, m_{\tau_{i-1}|i}^{(m)}, N_i^{(m)}, (q_i^A)^{(m)})$$

- Attach weights to the particles as

$$w_{i,2}^{(m)} = p(c_i^A > 0 \mid a_{\tau_i}^{(m)}, m_{\tau_i}^{(m)}, (q_i^A)^{(m)})$$

- Sample from the truncated normal distribution

$$(c_i^A)^{(m)}) \sim f(c_i^A \mid c_i^A > 0, a_{\tau_i}^{(m)}, m_{\tau_i}^{(m)}, (q_i^A)^{(m)})$$

Particle Filter, Step 4

- Resample the particle set according to the probability $\pi_i^{(m)} = \frac{w_i^{(m)}}{\sum_{m=1}^{M} w_i^{(m)}}$ to yield M equal-weighted particles denoted by $(m_{\tau_{i-1}|i}^{(m)}, N_i^{(m)}, (q_i^A)^{(m)})$. $w_i^{(m)} = w_{i,1}^{(m)} \times w_{i,2}^{(m)}$
- One can then proceed to marginalize m_{τ_i} to represent the filtering distribution $f(m_{\tau_i} \mid \mathcal{D}_i)$
- The likelihood value can be computed as

$$\begin{aligned} P(A_{\tau_i} \mid \mathcal{D}_{i-1}, c_i^A > 0) &= \frac{P(c_i^A > 0 \mid \mathcal{D}_{i-1}, A_{\tau_i}) P(A_{\tau_i} \mid \mathcal{D}_{i-1})}{P(c_i^A > 0)} \\ &\approx \frac{\frac{1}{M}\sum_{m=1}^{M} w_i^{(m)}}{P(c_i^A > 0)} \end{aligned}$$

Parameter Estimation: Monte Carlo EM algorithm

- The particle filter gives a point-by-point estimate of the likelihood function, but straightforward optimization is not possible (irregularity due to the resampling step)
- Instead, use a Monte Carlo version of the EM algorithm to obtain the ML estimates. Here filtering is done in the E-step and optimization in the M-step thus the irregularity is not consequential

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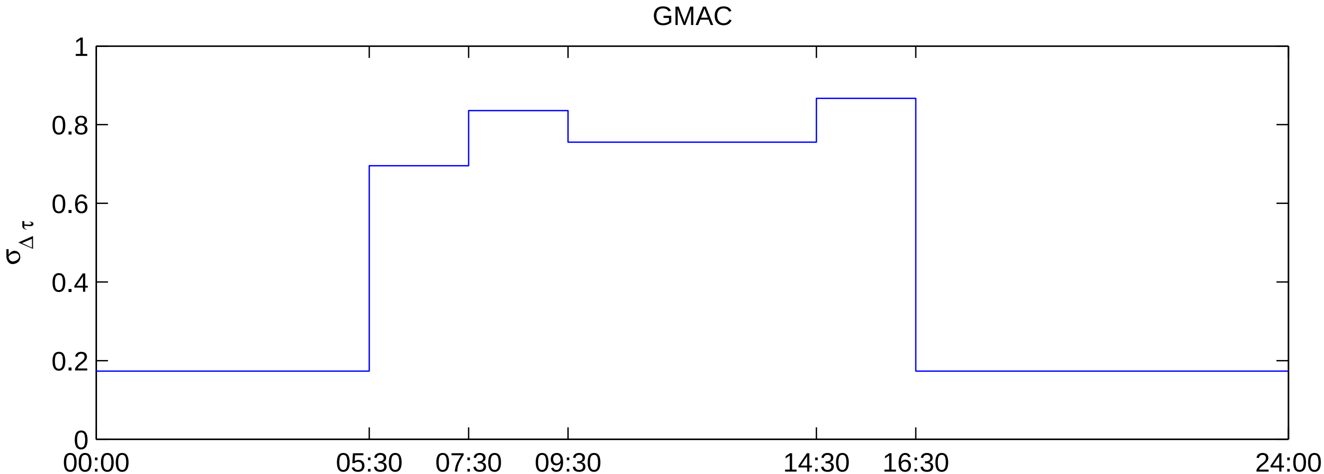
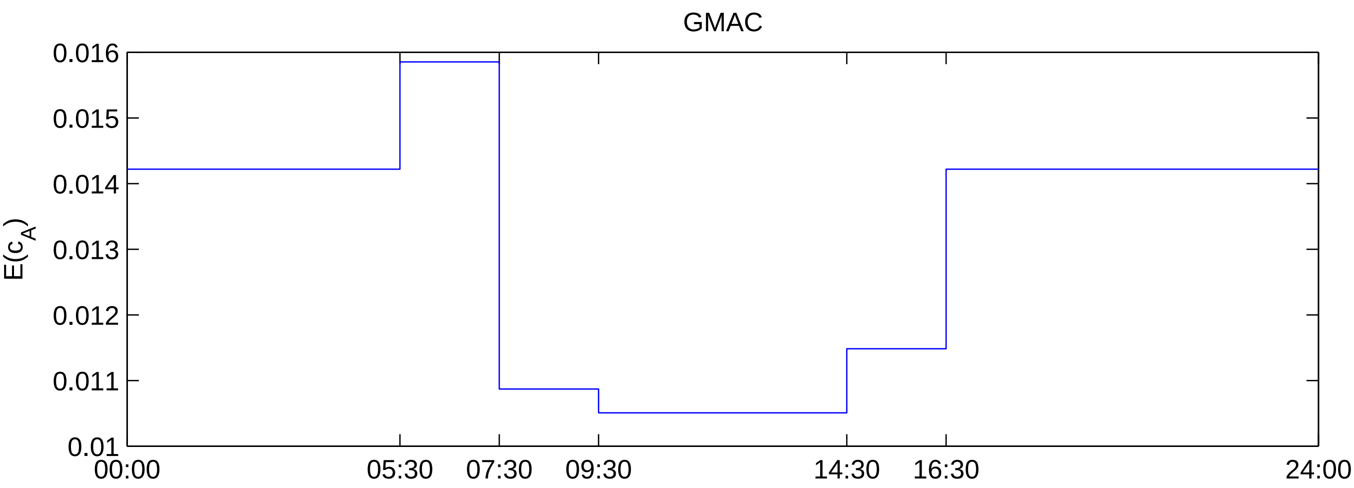
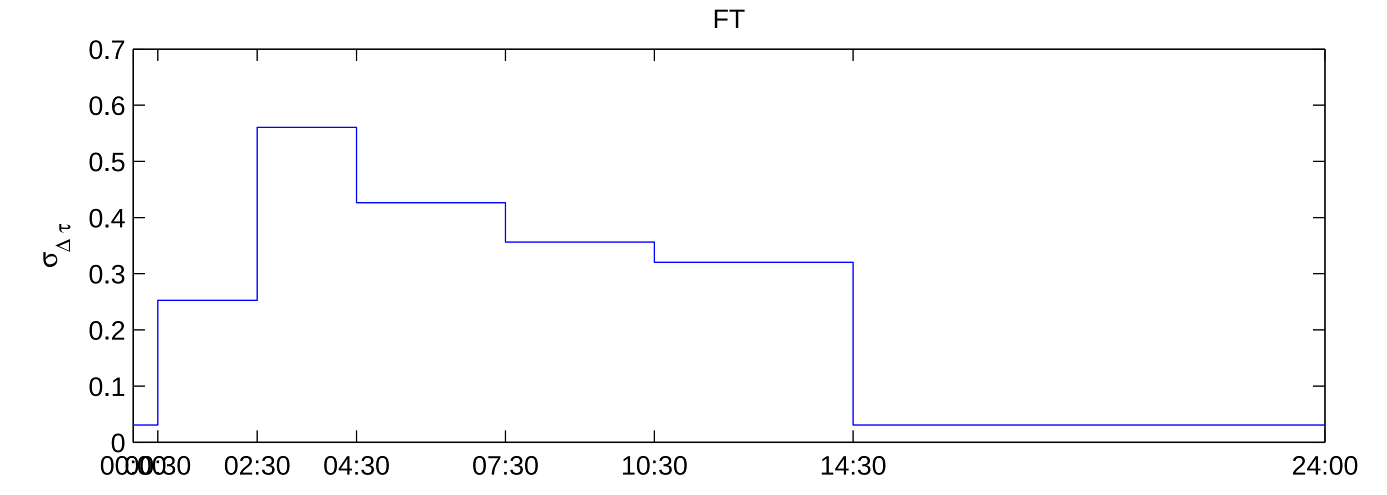
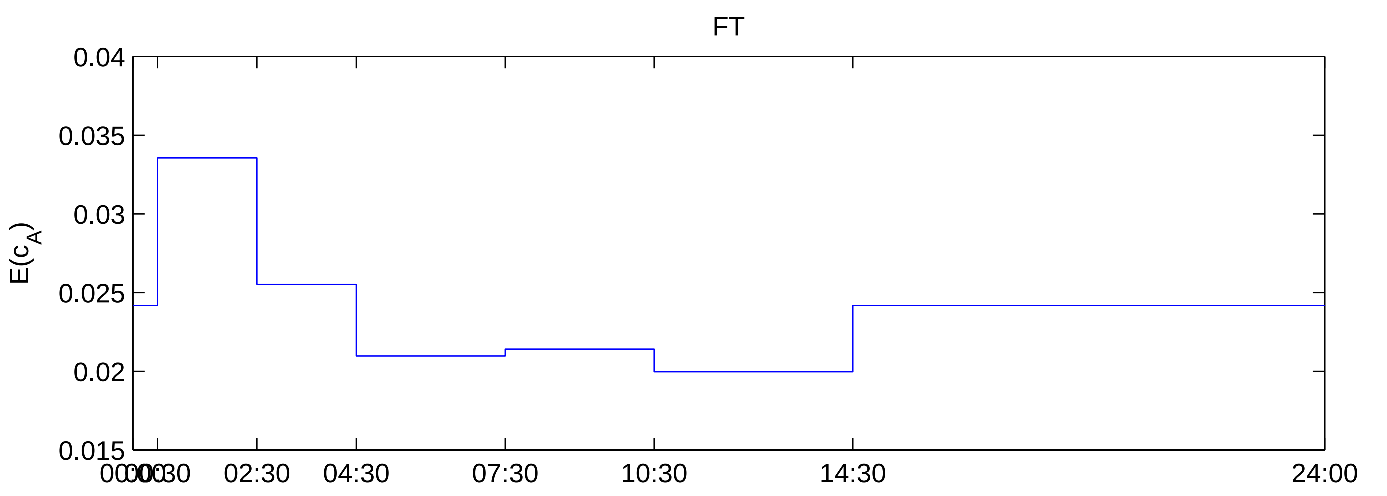

GMAC
1
0.8
0.6
0.4
0.2
0
$\sigma_{\Delta\tau}$
00:00
05:30
07:30
09:30
14:30
16:30
24:00


GMAC
0.016
0.015
0.014
0.013
0.012
0.011
0.01
$E(c_A)$
00:00
05:30
07:30
09:30
14:30
16:30
24:00


FT
σ Δτ
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
00:00
00:30
02:30
04:30
07:30
10:30
14:30
24:00


FT
E(c A)
0.04
0.035
0.03
0.025
0.02
0.015
00:00
00:30
02:30
04:30
07:30
10:30
14:30
24:00

Summary of estimation results

- Volatility exhibits the usual J-shaped pattern during the day, with a decrease in the overnight period
- Transaction costs exhibit J-shaped pattern during the day, with an increase in the overnight period
- Transaction costs peak before volatility

Table 3

Panel A: US names

Time	Ford σ_u	Ford μ	GMAC σ_u	GMAC μ	Sears Acceptance σ_u	Sears Acceptance μ
05:30-07:30	0,6085	0,0054	0,6954	0,0069	0,1974	0,0282
	0,0338	*0,0010*	*0,0572*	*0,0010*	*0,1379*	*0,0035*
07:30-09:30	0,7093	-0,0102	0,8356	-0,0066	0,6991	0,0084
	0,0315	*0,0016*	*0,0322*	*0,0015*	*0,0918*	*0,0034*
09:30-14:30	0,6028	-0,0068	0,7555	-0,0079	0,7135	-0,0080
	0,0260	*0,0015*	*0,0254*	*0,0014*	*0,0724*	*0,0045*
14:30-16:30	0,6158	-0,0044	0,8669	-0,0045	0,6299	-0,0126
	0,0426	*0,0017*	*0,0569*	*0,0015*	*0,1972*	*0,0070*
16:30-05:30	0,1958	-0,0037	0,1735	0,0032	0,2017	-0,0694
	0,0132	*0,0020*	*0,0232*	*0,0016*	*0,0326*	*0,0586*
Parameters						
$\sigma_{c,A}$	0,0166		0,0163		0,0380	
	0,0005		*0,0005*		*0,0019*	
$\sigma_{c,B}$	0,0159		0,0174		0,0403	
	0,0005		*0,0005*		*0,0016*	
σ_ϵ	0,0816		0,0844		0,2071	
	0,0034		*0,0031*		*0,0251*	
λ	0,1578		0,1483		0,1222	
	0,0108		*0,0080*		*0,0185*	
μ_J	0,4142		0,1123		1,8867	
	0,2386		*0,2627*		*0,9282*	
σ_J	5,8427		6,2286		9,3800	
	0,2084		*0,2014*		*0,9730*	

Table 3 Panel B: European name

	France Telecom	
Time	σ_u	μ
00:30-02:30	0,2526	0,0267
	0,0353	*0,0014*
02:30-04:30	0,5606	0,0124
	0,0512	*0,0013*
04:30-07:30	0,4262	0,0018
	0,0462	*0,0018*
07:30-10:30	0,3564	0,0030
	0,0380	*0,0018*
10:30-14:30	0,3202	-0,0009
	0,0363	*0,0023*
14:30-00:30	0,0306	0,0095
	0,0523	*0,0049*
Parameters	#N/A	#N/A
$\sigma_{c,A}$	0,0254	
	0,0008	
$\sigma_{c,B}$	0,0253	
	0,0008	
σ_{ϵ}	0,0598	
	0,0053	
λ	0,2879	
	0,0243	
μ_J	-0,0484	
	0,1921	
σ_J	5,0601	
	0,3840	

Conclusions

- Transaction costs for CDS's are not substantially lower than their counterparts in corporate bond markets
- We do not find much evidence in our data for the inventory paradigm.
- Between 7.30-9.30 we observe a period with high volatility, high volume but low transaction costs. This is consistent with Admati and Pfeiderer (1988).
- The J-shape pattern of volatility and transaction costs may signal the presence of the price discovery process
- More research is needed on this issue, especially to disentangle the asymmetric information story from price competition among dealers