Residential Mortgage Credit Derivatives

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Residential mortgage credit risk

- Economically significant - $11 trillion
- Limitations of the existing hedging tools
  - Mortgage insurance contracts
    - Limited capitalization of mortgage insurers
    - Only the first loss position
  - Securitization
    - Bundling of securitization and guarantee
    - Agency securitization is only for conformable loans
  - Currently traded OTC derivative contracts (ABX.HE) and house price derivatives (CME)
    - Basis risk

New instruments may improve the efficiency of the system

- Example: ARMs held as whole loans - $3 trillion
  - No need for dynamic hedging (+)
  - Loss reserves versus marked-to-market (+)
  - Selling is less consequential (+)
  - Overexposure to regional fluctuations (-)
  - Worse capital requirement than securities (-)

- Hedging without the drawbacks of existing ones
  - Help depositories hold whole loans and enjoy of smaller capital requirements and diversification

Contribution

- Propose derivatives based on the credit losses of a reference mortgage pool
  - Do not have the same limitations as mortgage insurance and securitization
- Analyze the basis risks of these contracts
  - Theoretical analysis (simulations of a theoretical model of default)
  - Empirical analysis (LoanPerformance data)
  - Standard measure of basis risk (adjusted-R^2)
  - Benchmark basis risk with house-price derivatives

Summary of Conclusions

- Static hedges in simulations with
  – Loss based index (R^2 = 86%)
  – House-price index (R^2 = 32%)
- Static hedges in empirical analysis with
  – Loss based index (adj-R^2 = 17%)
  – House-price index (adj-R^2 = 10%)
- Simple dynamic hedges with house-price index
  – In simulations (R^2 = 46%)
  – In empirical analysis (adj-R^2 = 12%)

Related Literature

- House-price index to hedge credit risk
  - Case and Shiller (1996)
- House-price index use by consumers
  - Englund, Hwang, and Quigley (2002), Shiller (2007), de Jong, Driessen, and Hemert (2008), Deng and Quigley (2007), Clapham, Englund, Quigley, and Redfearn (2006)
- Moral hazard and adverse selection in credit
  - Gan and Mayer (2007) and Duffee and Zhou (2001)

The Hedged Variable

- Let the credit loss of a mortgage i at time t be

$$Loss_{i,t} = \langle \begin{array}{ll} 0 & \text{if there is no default at t} \\ L_i \times B_i & \text{otherwise} \end{array}$$

- Where L_i and B_i are the loss severity and the balance of origination of mortgage i
- The loss per unpaid original balance is of a portfolio is

$$Loss\_OUPB_t^{\Pi} = \frac{\sum_{i=1}^{N} Loss_{i,t}}{\sum_{i=1}^{N} B_i}$$

- N is the number of loans at the origination of the portfolio

The Hedge Ratios

- Static hedge - buy n_0^{Π} contracts at time zero of a contract that generates the cash flow f_t for all t between 1 and T.

- Minimize the variance of the hedged portfolio cash flows

$$n_0^{\Pi} = -(\sum_{i=1}^{N} B_i) \times \frac{\operatorname{cov}(Loss\_OUPB_t^{\Pi}, f_t)}{\operatorname{var}(f_t)} = -(\sum_{i=1}^{N} B_i) \times \beta_0^{\Pi, f}$$

- Dynamic hedge - buy n_t^{Π} contracts at time t of a contract that generates the cash flow f_{t+1} at t +1

$$n_t^{\Pi} = -(\sum_{i=1}^{N} B_i) \times \beta_t^{\Pi, f}$$

The Hedge Instruments and Effectiveness

- A derivative with cash flows based on the credit losses of a reference pool

$$CF_t = Index_t = \frac{\sum_{i=1}^{N_{Index}} Loss_{i,t}}{\sum_{i=1}^{N_{Index}} B_i}$$

- A derivative paying the appreciation in the house-price index between t-1 and t

$$CF_t = HPI_t = (\frac{S_t}{S_{t-1}} - 1)$$

- Analyzing hedging effectiveness

$$Loss\_OUPB_t^{\Pi} = \alpha + \beta^{\Pi,i} CF_t^i + \varepsilon_t$$

Simulations

- Simulate a portfolio of 1,000 loans and a reference pool with 10,000 loans
- Property values
  - follow a geometric Brownian motion
  - correlated with a house-price index. (ρ = 50%)
- Mortgage default happens when house price drops below a certain level D
- Estimate the hedging effectiveness regression for each simulation

Simulation – Table 1

	1	2	3
INTERCEPT	0.0004	2.7E-06	3.1E-06
	(7.65)	(0.14)	(0.16)
HPI	-0.0057		-5.6E-05
	(-4.99)		(-0.14)
INDEX		0.9802	0.9795
		(57.90)	(55.70)
R2	0.0683	0.8639	0.8643
Adjusted-R2	0.0683	0.8639	0.8639

Improving HPI performance

- Losses are non-linear function of AGE
  - Control for AGE and AGEDUM (dummy =1 if AGE smaller than 9 months, zero otherwise)
  - HPI hedge ratio change with AGE and AGEDUM

- Mortgage loans are like put options on HPI
  - HPI hedge ratio change with CHPIDUM (dummy = 1 if cumulative HPI since origination is smaller than -1% and zero otherwise)

Simulation – Table 1

	4	5	6	7	8	9
INTERCEPT	0.0010	7.5E-06	8.7E-06	0.0003	0.0003	0.0009
	(11.34)	(0.18)	(0.20)	(7.77)	(7.89)	(12.88)
HPI	-0.0053		-6.0E-05	-0.0039	-0.0118	-0.0116
	(-5.61)		(-0.15)	(-3.37)	(-4.77)	(-6.03)
INDEX		0.9808	0.9797			
		(48.95)	(46.56)			
AGE x AGEDUM	0.0003	-8.7E-06	-8.2E-06			0.0003
	(4.49)	(-0.26)	(-0.25)			(5.42)
AGE	-3.5E-06	-2.4E-08	-2.8E-08			-3.4E-06
	(-8.46)	(-0.13)	(-0.15)			(-9.85)
HPI x CHPIDUM				-0.0093	-0.0017	-0.0061
				(-2.67)	(-0.75)	(-1.74)
AGE x HPI					4.3E-05	4.5E-05
					(3.82)	(5.07)
AGEDUM x HPI					-0.0057	-0.0044
					(-2.92)	(-2.81)
R2	0.3199	0.8669	0.8673	0.1123	0.2133	0.4569
Adjusted-R2	0.3161	0.8662	0.8662	0.1098	0.2067	0.4492

Data

- LoanPerformance Data
  - More than 4 million securitized subprime mortgages originated from 1997 to 2006
  - Origination balance, LTV, FICO, credit grade, losses due to REO or short sale
- OFHEO house-price indexes
  - Repeat sale, quarterly, state indexes

Empirical Analysis

$$Loss\_OUPB_t^{\Pi} = \alpha + \beta^{\Pi,i} CF_t^i + \varepsilon_t$$

- LHS – losses of a pseudo portfolio
  - Pseudo portfolio - all the loans in a given pool with a given origination year and state
- RHS
  - INDEX of losses of a reference pool with all mortgages in a given state and origination year
  - OFHEO HPI
  - AGE, AGEDUM, CHPIDUM
  - Lagged INDEX and HPI

Empirical Results – Static Hedging

	1	2	3	4	5	6	7	8
INTERCEPT	0.0012	0.0001	0.0001	0.0012	0.0001	0.0007	0.0002	0.0001
	(3.08)	(0.30)	(0.30)	(2.97)	(0.28)	(0.38)	(0.01)	(0.00)
HPI_t	0.0096		0.0064	0.0429		0.0083		0.0028
	(-0.05)		(-0.08)	(0.21)		(0.11)		(0.10)
$INDEX_t$		0.8464	0.8643		1.0240		1.0310	1.0361
		(1.91)	(1.94)		(0.83)		(1.60)	(1.58)
HPI_{t-1}				-0.0429				
				(-0.24)				
HPI_{t-2}				-0.0116				
				(-0.02)				
HPI_{t-3}				0.0065				
				(-0.17)				
$INDEX_{t-1}$					-0.0978			
					(-0.17)			
$INDEX_{t-2}$					0.0533			
					(0.16)			
$INDEX_{t-3}$					-0.1797			
					(-0.02)			
AGE x AGEDUM						5.4E-05	-1.4E-05	-1.5E-05
						(1.05)	(-0.11)	(-0.13)
AGE						-5.7E-06	-7.3E-06	-7.5E-06
						(0.34)	(0.22)	(0.22)
R^2	0.0450	0.1306	0.1767	0.1274	0.2354	0.1616	0.2206	0.2479
Adjusted-R^2	0.0450	0.1306	0.1500	0.0356	0.1564	0.1054	0.1685	0.1697
Obs.	49	49	49	49	49	49	49	49

Empirical Results – Dynamic Hedging

	9	10
INTERCEPT	0.0012	0.0005
	(3.13)	(0.25)
HPI_t	-0.0281	-0.1823
	(-0.44)	(-0.47)
HPI x CHPIDUM	0.1109	0.0404
	(0.75)	(0.41)
AGE x AGEDUM		7.0E-05
		(1.01)
AGE		6.5E-07
		(0.40)
AGE x HPI		0.0047
		(0.27)
AGEDUM x HPI		0.0069
		(0.52)
R^2	0.0845	0.2574
Adjusted-R^2	0.0547	0.1197
Obs.	49	49

Conclusion

- Derivatives based on loss-based indexes
  - May allow depositories to achieve the economic benefits of hedging while holding portfolios of whole loans
  - The basis risk of static hedges made with these derivatives is smaller than the basis risk made with simple dynamic hedges using HPI
- Further research to improve the hedge effectiveness of loss-based indexes

Improving Hedge Effectiveness

Use weights to match reference pool characteristics to pseudo pool

- Partition loans in both reference and pseudo into categories by the following
  - Origination year, state (aggregated), Origination amount>$75 k, Fixed vs. ARM, ARM 2-28, Investor, Cashout, LTV>=80, FICO>=630, Risk Class B, and Risk Class C
- Base index on weighted reference pool losses
  - Weight = Ratio of origination amounts in pseudo pool to reference pool by category

Preliminary Results

- Weights
  - Number of pseudo pools: 1266
  - Distribution of non-zero weights across pools
    - Mean: 0.04
    - 95 percentile: 0.16
    - 99 percentile: 0.55
- Regression of pseudo pool losses on weighted reference pool losses
  - Average R2: 0.33
- Regression of summed pseudo pool losses on summed weighted reference pool losses
  - Average R2: 0.85