Article

Pricing Defaulted Italian Mortgages

Michela Pelizza and Klaus R. Schenk-Hoppé *

Department of Economics, University of Manchester, Manchester M13 9PL, UK;
Michela.Pelizza@postgrad.manchester.ac.uk
* Correspondence: klaus.schenk-hoppe@manchester.ac.uk

check for
updates

Abstract: Our paper forecasts the expected recovery rates of defaulted Italian mortgage loans backed by either residential or commercial real estate. We apply an exponential Ornstein–Uhlenbeck process to model the price dynamics at the provincial and regional level, and two haircut models to estimate the liquidation value. Compared to our findings, rating agencies such as Moody's, which use geometric Brownian motion to model the price dynamics, paint a rosier picture with higher recovery rates. As a consequence, non-performing mortgage loans held by Italian banks might be overvalued.

1. Introduction

Forecasting expected recovery rates of defaulted mortgage loans relies on modelling the stochastic price process (typically price per square meter of a specific property type) as well as possibly employing a realistic liquidation model. The recovery rate is the fraction of the value of an asset recovered from liquidating the collateral. For real estate mortgages, the collateral is typically the value of the property. Our aim is to forecast expected recovery rates of defaulted Italian mortgage loans backed by either residential or commercial real estate.

Moody's Investors Service (2004, 2019) valuation model of defaulted Italian mortgages is based on the assumption that prices per square meter follow a geometric Brownian motion, a popular model to describe stock prices. However, Fabozzi et al. (2012) and Perelló et al. (2008) found that an exponential Ornstein–Uhlenbeck (EOU) process is more suitable for modelling the stochastic dynamics of real estate prices. Property price dynamics are important as they capture the loan-to-value ratio, which in turn determines loss given default and thus the recovery rate.[1]

In this paper, we use a unique data set of real estate prices in all Italian provinces collected by the Agenzia delle Entrate—Osservatorio del Mercato Immobiliare. We calibrate an EOU process and estimate the recovery rate of defaulted mortgages. Recovery rates depend, in addition to the property price dynamics, on the length of legal procedures to liquidate the property after default and on the actual liquidation value. In Italy the length of legal procedures varies considerably between provinces, which explains in part the sluggish recovery of the Italian economy since the 2008 financial crisis.[2]

Expected recovery rates vary significantly across provinces due to different price dynamics, and these rates become even more variable when including the specific court timings in the analysis. This is especially true for the lower tail of the distribution (i.e., recovery rates significantly worsen in

---

[1] See also Gao et al. (2009) and Chaiyapo and Phewchean (2017) on mean reversion and the use of EOU in modelling house prices. Blanco and Gimeno (2012) show the importance of loan-to-value in defaults.

[2] For macro-prudential regulation the correct estimation and pricing of risks related to mortgages plays a pivotal role, see, for example, Ye and Bellotti (2019); Ferretti et al. (2019); and Mayer et al. (2009).

magnitude for less efficient provinces). A portfolio of bad loans produced a very different cash flow depending on the efficiency of the legal courts that manage the foreclosure.

Actual liquidation of property in Italy happens at auctions.[3] Banks reduce the sale price with every subsequent auction, until the property is sold. We consider a simple model of liquidation value, common in real estate literature, where a haircut of 20% is assumed; in other words, the proceeds from selling the property are on average equal to 80% of the property's the market price (this discount also includes other legal costs). We also use Moody's liquidation model where the discount in each round of auctions and the number of auctions is taken into account. This approach allows us to determine how sensitive recovery rates are with respect to the assumption on the underlying price dynamics and the role played by the liquidation model.

Moody's, which publishes results by regions rather than the more detailed provincial level, reported range of expected recovery rates is smaller than ours. Their recovery rates are consistently biased upward, with larger discrepancies among more volatile regional markets. Compared to our model, Moody's underestimates expected loss given default on those markets, especially for less developed regions. Of course, considerable model risk remains as none of the competing stochastic models is correct. A more suitable model should produce results closer to the truth in the particular task at hand. An ambitious project, left for future research, is to compare forecasted and actual recovery rates. However, such a project likely requires the involvement of the Bank of Italy or a major commercial Italian bank since access to reliable data will be an issue.

Our paper also observes high volatility in recovery rates across Italian provinces, a factor that seems to be overlooked by large rating agencies. Indeed, Moody's assumes that the provinces in each of Italy's 20 regions have similar characteristics, but huge discrepancies in the stochastic dynamics of collateral prices are observed at the municipal level, resulting in overoptimistic forecasts and expected recovery rates on Italian impaired mortgages that are too high. Our results also suggest that the Bank of Italy does not correctly address the riskiness characterizing those exposures. As a consequence, equity provisions that Italian banks need to keep according to Basel III requirements might be miscalculated. Market practitioners have to adjust coarse regional recovery rates to account for these substantial intra-regional differences. Without correctly quantifying the riskiness of the defaulted mortgages held on their balance sheets, banks might not make enough provisions of non-performing loans and violate Basel III recommendations. Given that risk-based pricing is now more widespread in Italy (Magri and Pico 2011), adequate assessment of riskiness is vital to a sound banking sector.

These findings are important because the stock of non-performing loans (NPLs) in Italy tripled since the 2008 global financial crisis, reaching 18% of total loans in 2015 (Bank of Italy reports by Ciocchetta et al. 2017; Accornero et al. 2017; Fischetto et al. 2018). The NPL problem at Italy's banks is largely the result of the prolonged recession that hit the Italian economy in recent years and of lengthy credit recovery procedures (European Banking Authority 2016). In addition to rising concerns about the soundness of the banking sector, this phenomenon might trigger a vicious circle where the contraction in credit supply driven by the level of NPLs leads to lower growth, a slower recovery, and a further deterioration in the balance sheets. In March 2018 the European Commission adopted a comprehensive package of measures, including a proposal for a regulation amending the Capital Requirements Regulation (CRR) to introduce common minimum loss coverage levels for newly originated loans that become non-performing (European Systemic Risk Board 2017a, 2017b).

Figures are produced using Mapchart.net. This paper is based on the first author's MSc dissertation which was supervised by the second author at the University of Manchester in summer 2019.

---

[3]   For a detailed account see Giacomelli et al. (2018).

2. Data and Model

2.1. Data

The main data used in this study consist of the Property Market Observatory (OMI, *Organizzazione Mercato Immobiliare—Agenzia delle Entrate*) data set. The data contain the time series of house prices from H1:2000 to H1:2018, collected on a half-yearly basis. Each time series provides minimum house price per square meter (psqm) and the maximum house price psqm. Each price range is associated to a specific municipality (9714 municipalities), in the respective province (107 provinces), region (20 regions), and territorial area (north-west, north-east, centre, south and isles) of Italy.

Each range of prices is specific to qualitative characteristics: property location, property maintenance status, and property type. Some data cleaning is performed in order to get every half-yearly time series comparable to each other, since data collection and notation changed during the sample period. We use the average of the minimum and the maximum psqm as an approximation of the fair price.

The data set provided by OMI also includes a more detailed breakdown into collateral geographic location (ISTAT[4] code, OMI code) and range of monthly lease rent prices psqm. Since this information is not relevant for the purpose of this research, such data columns are not considered.

Court-by-court data on the length of Italian legal procedures are obtained from *La durata dei fallimenti e delle esecuzioni immobiliari e gli impatti sui npl*, a Cerved Group S.p.A. ("La Scala" Attorneys Association) study, allowing for a very detailed calibration analysis and the estimation of expected recovery rates forecast from the foreclosure of the collateral backing the defaulted loans.

We provide an overview of the data for residential properties in Figure 1 which shows average prices (psqm) at the provincial level. Northern and central Italian provinces have higher average prices than southern and island provinces. The most expensive provinces are Roma (€6291), Milano (€5190), Venezia (€4544), Siena (€4329), and Bolzano (€4042), followed by Firenze (€3345) and Bologna (€3255). Among southern cities, only Napoli (€4449) and Salerno (€3269) are among the most expensive Italian cities. Lowest average prices (psqm) are found in Caltanissetta (€661), L'Aquila (€750), Ragusa (€856), and Trapani (€883). Lower-than-average prices in L'Aquila are partly due to the frequent occurrence of earthquakes in that area.

2.2. Model

The model consists of two main elements: (1) a stochastic continuous-time model capturing the dynamics of prices per square meter of real estate (psqm); and (2) a valuation model for recovery rates of real estate loans at the time of default.

The stochastic dynamics of prices are described by an exponential Ornstein–Uhlenbeck (EOU) process as proposed in Fabozzi et al. (2010) and Perelló et al. (2008). [5] Both papers provide strong support for this model. The EOU of the psqm P_t is given by the stochastic differential equation

$$dS_t = \theta(\mu - S_t)dt + \sigma dW_t \tag{1}$$

S_t is the log of psqm P_t, μ is the (long-run) trend, $\theta \geq 0$ measures the speed of mean reversion, σ is the volatility and, W_t is the Wiener process. The market value of the collateral of a loan that has market value P_t at time t evolves as

$$P_T = P_t e^{S_T}$$

for all $T \geq t$.

---

4   ISTAT—Istittuto Nazionale di Statistica.
5   See also Qi and Zhao (2011) for a comparison of different loss-given default models. Van Damme (2011) provides a more general framework than considered here which might be of interest in further empirical studies.
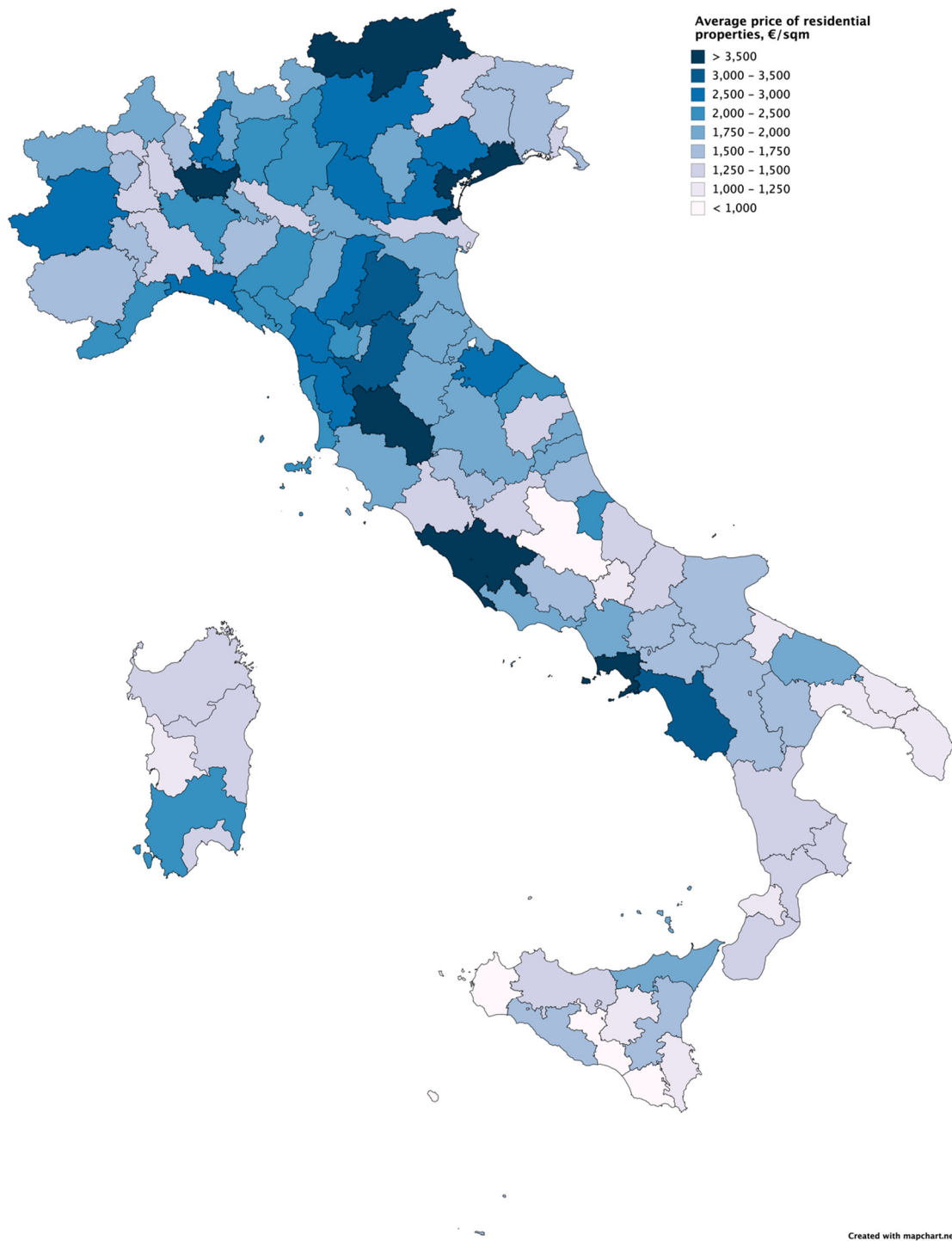
Figure 1. Average price of residential properties (€ per square meter). (Mapchart.Net 2020).

Applying Ito's lemma, one obtains

$$dP_t = (\theta(\mu - \ln P_t) + \frac{1}{2}\sigma^2)P_t dt + \sigma P_t dW_t \tag{2}$$

In Monte Carlo simulations, one can use the discrete-time approximation

$$P_t = P_{t-1} + \left(\theta(\mu - \ln P_{t-1}) + \frac{1}{2}\sigma^2\right)P_{t-1}\Delta t + \sigma P_{t-1}\sqrt{\Delta t}\,\Delta W_t \tag{3}$$

Converting to returns, we finally find:

$$R_t = \left(\theta\mu + \frac{1}{2}\sigma^2\right)\Delta t - \theta \,\Delta t \ln P_{t-1} + \sigma \,\epsilon_t \,\Delta t \tag{4}$$

with $\epsilon_t \sim N(0,1)$. The length of time steps Δt is six months because our data are provided on a semi-annual basis. Equation (5) can be written as a regression formula:

$$R_t = \alpha + \beta \,\ln P_{t-1} + e_t \tag{5}$$

where $\alpha = \left(\theta\mu + \sigma^2/2\right)\Delta t$, $\beta = -\theta\Delta t$, and $e_t = \sigma\epsilon_t\Delta t$.

This gives us the following ordinary least squares (OLS) parameter estimates:

$$\hat{\theta} = -\frac{\beta}{\Delta t}, \quad \hat{\sigma} = \sqrt{\sigma_e^2/\Delta t}, \text{ and } \hat{\mu} = \left(\sigma_e^2/2 - \alpha\right)/\beta.$$

σ_e^2 is the variance of the error term e_t (Iacus 2008).

Recovery rates are calculated from a loan's loss profile

$$LP_{T_D} = \max\left\{EAD - \exp(-r(T_L - T_D))\,(1-k)\,P_{T_L},\, 0\right\} \tag{6}$$

T_D is the time of default, T_L the time of liquidation of the collateral, r the discount rate (market interest rate), EAD is exposure at default (the outstanding unredeemed part of the loan at time of default), k is a discount applied to the collateral which has market value P_{T_L} at the time of liquidation. The discount k captures losses (relative to the market price) due to property being sold at auction and other legal and administrative costs.

The expected loss given default (the loss per Euro exposed at default), is given by

$$LGD_{T_D} = \frac{\mathbf{E}\,LP_{T_D}}{EAD} \tag{7}$$

where the expectation $\mathbf{E}\,LP_{T_D}$ is the integral over (Equation (6)) under the distribution of P_{T_L} which is defined by the dynamics (Equation (3)) with initial value P_{T_D}. The time span between the initial and the terminal time is $T_L - T_D$, the time between the default and the liquidation. Unlike in option pricing models, the expectation is taken under the physical measure.

The (expected) recovery rate is finally given by

$$RR_{T_D} = 1 - LGD_{T_D} \tag{8}$$

Frontczak and Rostek (2015) derive explicit equations for these quantities. Their remark in Section 3.2 states that

$$LGD_{T_D} = \Phi(d) - (1-k)\,e^{-r(T_L - T_D)}\,\frac{P_{T_D}}{EAD}\,e^{\mu_Y + \frac{\sigma_Y^2}{2}}\,\Phi(-(d + \sigma_Y))$$

where

$$d = \frac{ln\left((1-k)\,\frac{P_{T_D}}{EAD}\,e^{-r(T_L - T_D)}\right) + \mu_Y}{\sigma_Y}$$

$$\mu_Y = \mu - \left(\mu - S_{T_D}\right)e^{-(T_L - T_D)}\quad \sigma_Y^2 = \frac{\sigma^2}{2}\left(1 - e^{-2(T_L - T_D)}\right)$$

and S_{T_D} is the log price. Φ is the cumulative normal distribution. One can use these formulas to determine recovery rates (after calibration of the model to find the parameters μ, σ, and θ). Alternatively,

one can also carry out Monte Carlo simulations.[6] In our case both produce essentially identical results with 100,000 runs.

We estimated loss given defaults (LGDs) directly in terms of the loan-to-value ratio. This quantity is defined as the ratio of the face value of debt and the collateral value pledged against the debt, EAD/P_t. This ratio is used by banks to assess the riskiness of an engagement. The more collateral is provided, the less potential losses in case of default (i.e., prices are risk-sensitive).

The time between the default of an obligor and the liquidation of the collateral, $T_L - T_D$, depends mainly on the length of legal proceedings. These durations vary considerably across Italy. Sicilia and Molise have the least efficient courts in the entire country with foreclosures taking on average 18.5 years (Messina), 15.7 years (Enna), 14.7 years (Campobasso), and 14.6 years (Caltanissetta). In contrast, Crotone, Bolzano, Gorizia, and Como have the most efficient courts with 3.8, 4.1, 4.1, and 4.2 years, respectively (*La durata dei fallimenti e delle esecuzioni immobiliari e gli impatti sui npl*, Cerved Group S.p.A).

The wide variability observed in the courts' timing therefore affects the value of NPLs. A portfolio of bad loans produces a very different cash flow depending on the efficiency of the legal courts that manage the foreclosure. Longer legal proceedings become costlier and erode the current value of the collateral. All this results in even lower expected recovery rates, thus higher expected losses and tighter capital requirements for the already distressed Italian banks. The duration of real estate foreclosures has a pronounced impact on the value of impaired loans in the Italian banks' balance sheets because it affects the timing and size of recovery quotas on those credits.

The 'fire sale' discount k can be modelled in many different ways. In the Italian jurisdiction, the enforced properties are sold in auctions by the court. It is customary to assume a constant haircut of $k = 20\%$. The discount can also be based on the number of auctions it takes to sell the collateral and the haircut (i.e., the discount applied between subsequent auctions).[7]

Moody's Investors Service (2019) model describes real estate prices using a geometric Brownian motion process (GBM), defined by the stochastic differential equation

$$dP_t = \mu P_t dt + \sigma P_t dW_t \tag{9}$$

The growth rate μ and the volatility σ of the property values in the pool depend on the asset type (residential or commercial) and geographical location.

The cash flow generated by the liquidation of a pool of defaulted mortgages in secured transactions (amounts and timing of collections), at the point of sale, is the solution to Equation (9).[8]

$$\text{Proceeds from liquidation} = f_{adjusted} \, P_{T_D} \, e^{\left(\mu - \frac{\sigma^2}{2}\right)(t - T_D) + \sigma \sqrt{(t - T_D)}}$$

where $\varepsilon \sim N(0, 1)$. The adjustment factor $f_{adjusted}$ in Moody's model incorporates the timing of collections to factor into the analysis the possibility of longer-than-average recovery times. The adjustment also distinguishes between more liquid and less liquid properties (primarily determined by property location and condition). Moody's assumes that more than one auction may be required to sell fewer liquid assets. Thus, for each additional auction in the foreclosure process, property values are adjusted as set in the previous formula; Moody's applies fixed haircut levels in Italy to reduce the initial property value by 10% to 25%, depending on the region under consideration, for each additional auction (Moody's Investors Service 2019, p. 15). In this case,

$$f_{adjusted} = (1 - haircut)^{number \, of \, auctions - 1}$$

---

[6]　Numerical simulations can be based on, for example, the method detailed in Kuchuk-Iatsenko and Mishura (2015).
[7]　There is strong support for such a two-step approach (first price dynamics then applying a discount) over models aiming to directly capture the liquidation value (e.g., Leow and Mues (2012)).
[8]　LGDs in the geometric Brownian motion model can be calculated explicitly as in the Merton (1974) model.

is the estimated liquidation value relative to the market value.

2.3. Comparison of Price Process Models

An estimation of the three different stochastic processes is performed to assess which one provides the best fit of our data. This is done across geographical areas, but also distinguishes between residential and commercial properties. Table 1 supports our analysis. The table shows how higher statistically significant mean reverting parameter estimations are obtained when using the EOU process to model the collateral price.

Table 1. Estimation of three different stochastic processes for the collateral value across geographic areas. Real estate data H1:2000–H1:2018.

	Geometric Brownian Motion		Geometric Ornstein–Uhlenbeck Process			Exponential Ornstein–Uhlenbeck Process		
	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\theta}$	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\theta}$
North West	0.0036	0.0147	975.2997 log: 6.8827	0.0128	0.1458 ** (0.0445)	6.8838	0.0127	0.1504 ** (0.0454)
p-values on $\hat{\theta}$					0.0028			0.0025
North East	0.0082	0.0180	986.6739 log: 6.8947	0.0153	0.1150 ** (0.0323)	6.8871	0.0146	0.1312 *** (0.0327)
p-values on $\hat{\theta}$					0.0013			0.0004
Central	0.0037	0.0257	1137.5079 log: 7.0366	0.0243	0.0890 (0.0442)	7.0342	0.0244	0.0935 * (0.0458)
p-values on $\hat{\theta}$					0.0536			0.0498
South	0.0074	0.0256	738.2448 log: 6.6043	0.0144	0.0678 * (0.0253)	6.6034	0.0227	0.1242 ** (0.0420)
p-values on $\hat{\theta}$					0.0123			0.0062
Isles	0.0090	0.0205	759.2730 log: 6.6324	0.0108	0.0597 ** (0.0176)	6.6293	0.0167	0.1145 *** (0.0289)
p-values on $\hat{\theta}$					0.0020			0.0005

Notes: * *p*-value < 0.05, ** *p*-value < 0.01, *** *p*-value < 0.001.

The EOU process produces the best result. The mean reversion coefficient is consistently more significant than for the geometric OU process. *P*-values for the geometric Brownian motion are smaller across all geographic areas and for both property types. In conclusion, this analysis justifies the choice of the EOU as the stochastic process to model collateral values.

Calibration of the chosen EOU process model provides us with parameter values that will form the basis of our calculation of expected recovery rates. One can either use explicit formulas (given above) or run Monte Carlo simulations. When simulating the calibrated process, one can also visualize forecast housing prices data and the LGD distribution. In both approaches the outcomes are expected recovery rates for both residential and commercial real estate.

The calibration is performed using both maximum likelihood estimation (MLE) and least squares regression (LSE) methods. Both techniques are good at estimating drift and volatility. First, both estimates are unbiased. Second, the estimate of the standard deviation is accurate. The least-squares minimization is tested to verify the efficiency of the maximum likelihood estimation. Both provide the exact same parameter estimates for $\hat{\mu}$ and $\hat{\theta}$, but differ in estimating $\hat{\sigma}$. Thus, the root mean square error (RMSE) parameter is also provided and compared between the two methodologies.

The analysis follows the same structure as above: examining geographic areas before moving on to regions and finally provinces. In most cases, the RMSE parameter[9] is smaller when using the MLE than OLS: the only two exceptions are isles for residential properties (0.0173 vs. 0.0166) and north-west for commercial ones (0.0141 vs. 0.0133). However, this level of description is insufficient to justify the choice of the calibration model. For regions the MLE is also preferable to OLS because the MLE's RMSE is consistently smaller across all twenty Italian regions for commercial properties. For residential properties, the only exceptions are five regions out of twenty: Basilicata (0.0141 vs. 0.0136), Calabria (0.0200 vs. 0.0191), Sardegna (0.0265 vs. 0.0261), Toscana (0.0199 vs. 0.0194), and Veneto (0.0173 vs. 0.0170). Even in these few cases, the difference is very small. For the reasons discussed above, the MLE method is considered to be more efficient than the LSE method. The deepest level of analysis is performed only with the MLE technique.

3. Results

3.1. Expected Recovery Rates

Using the estimated parameter values, simulations of the exponential OU process are performed to forecast recovery rates for each region and each province of the Italian peninsula. The analysis is first carried out across regions for residential and commercial real estate separately. Average national recovery rates are 57.44% for residential property and 56.60% for commercial real estate. For residential properties recoveries range from 68.52% (Friuli Venezia Giulia and Trentino Alto Adige) to 38.60% (Molise). The ranking is the same for commercial property with Trentino Alto Adige at the top (68.31%), followed by Trentino Alto Adige (67.48%) and Valle d'Aosta (67.12%), while Molise is at the bottom of the distribution with 37.91%.

These intervals of 29.92 and 30.40 percentage points reveal significant inter-regional volatility. This becomes even more pronounced when splitting each region into its provinces. For the 108 Italian provinces we find the following: Gorizia and Bolzano come first with 75.05% both, followed by Como and Sondrio (74.53% both); the lowest are observed for Messina (27.39%), Enna (33.31%) and Campobasso (35.37%). The range widens to 39.16 percentage points between the most and least efficient provinces.

Figure 2 shows expected recovery rates for loans secured by residential properties. Commercial properties exhibit even larger differences between provinces than residential ones (available from the authors upon request). Indeed, recovery rates decreases more for southern and island regions than for northern ones.

It can be inferred from Table 2 that northern regions have smaller recovery rate intervals with respect to the rest: the province with the lowest recovery rate belongs to Sicilia (Messina with 27.39%), while the one with the highest recovery rate across the country is in Trentino Alto Adige (Bolzano with 75.05%), with a very pronounced difference of 47.66 percentage points. The very small range of recovery rates for Molise and Umbria (5.74 and 6.45 pp, respectively) are representative of a lower number of provinces in the region per se, together with consistently very low recovery percentages.

The situation does not change much when moving to commercial real estate (Table 3). Southern and central regions still show lower interval boundaries.

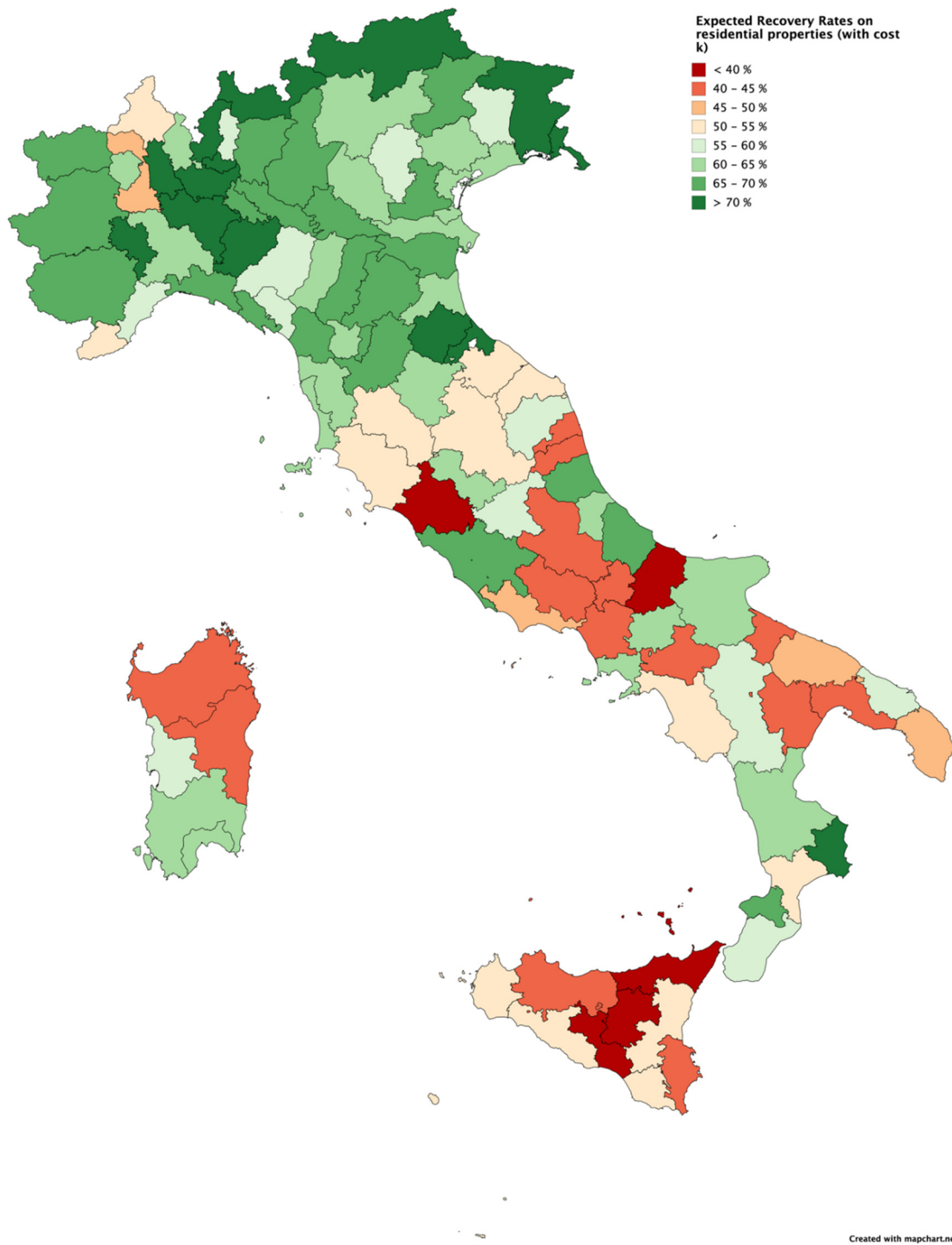[9]   See also Mejia Vega (2018) on calibration of EOU.

Figure 2. Expected recovery rates for residential properties. (Mapchart.Net 2020).

Table 2. Expected recovery rate intervals for residential properties across regions.

Region	Expected Recovery Rate Intervals (Residential)		
	Lower Bound	**Upper Bound**	**Interval Width (pp)**
Abruzzo	42.56%	68.05%	25.49
Basilicata	43.17%	56.72%	13.55
Calabria	53.63%	74.64%	23.01
Campania	40.25%	62.13%	21.88

Table 2. *Cont*.

Region	Expected Recovery Rate Intervals (Residential)		
	Lower Bound	**Upper Bound**	**Interval Width (pp)**
Emilia Romagna	58.33%	73.49%	15.16
Friuli Venezia Giulia	55.93%	75.05%	19.12
Lazio	38.58%	68.05%	29.47
Liguria	52.16%	69.49%	17.33
Lombardia	55.52%	74.53%	19.01
Marche	44.39%	56.72%	12.33
Molise	35.37%	41.11%	5.74
Piemonte	45.34%	73.49%	28.15
Puglia	44.09%	61.26%	17.17
Sardegna	42.23%	62.56%	20.33
Sicilia	27.39%	54.39%	27.00
Toscana	50.36%	69.98%	19.62
Trentino Alto Adige	62.80%	75.05%	12.25
Umbria	54.39%	60.84%	6.45
Valle d'Aosta	68.05%	68.05%	-
Veneto	58.32%	68.52%	10.20
Min	27.39%	41.11%	5.74
Max	68.05%	75.05%	29.47
Average	**48.64%**	**65.71%**	**18.07**

Table 3. Expected recovery ate intervals for commercial properties across regions.

Region	Expected Recovery Rate Intervals (Commercial)		
	Lower Bound	**Upper Bound**	**Interval Width (pp)**
Abruzzo	41.89%	68.04%	26.15
Basilicata	42.12%	55.89%	13.77
Calabria	52.01%	72.51%	20.50
Campania	40.01%	59.26%	19.25
Emilia Romagna	57.84%	73.47%	15.63
Friuli Venezia Giulia	55.83%	74.23%	18.40
Lazio	38.29%	68.04%	29.75
Liguria	50.65%	68.73%	18.08
Lombardia	57.41%	74.54%	17.13
Marche	42.27%	56.32%	14.05
Molise	35.73%	40.06%	4.33
Piemonte	44.39%	71.27%	26.88
Puglia	44.08%	59.62%	15.54
Sardegna	42.86%	61.46%	18.60
Sicilia	26.83%	53.28%	26.45
Toscana	49.41%	68.97%	19.56
Trentino Alto Adige	63.00%	74.12%	11.12
Umbria	53.28%	59.83%	6.55
Valle d'Aosta	67.44%	67.44%	-
Veneto	57.43%	67.51%	10.08
Min	26.83%	40.06%	4.33
Max	67.44%	74.54%	29.75
Average	**48.14%**	**64.73%**	**17.46**

3.2. Comparison with Moody's Valuations

We compare our results to Moody's rating practice. Moody's is chosen because it is one of the biggest rating agencies worldwide, owning around 40% of the market, and it provides detailed information on its credit rating methodology which enables us to derive expected recovery rates for regions following its procedure.

To perform the benchmark analysis with Moody's practice on evaluating stochastic collateral amounts on secured loans in the Italian territory, we use "Moody's Approach to Rating Securitizations Backed by Non-Performing and Re-Performing Loans" and "Moody's Approach to Rating Italian RMBS". These publications provide specific information about Moody's assumptions about the Italian market. It is important to stress that Moody's does not breakdown its assumptions at a province level but considers only inter-regional differences. Since the Italian real estate market is characterized by significant inter-regional differences (different provinces belonging to the same region show different price volatility and courts timing), the lack of information at province level constrains us to focus on the regional level.

To estimate the cash flows generated by a pool of secured NPL transactions, the model used in Moody's rating process generates the collected amounts and the timing of collections. Moody's calculates the stochastic collected amounts from the collateral by using a geometric Brownian motion to model future property values. Average price growth rates and their volatility are calculated from forecasted prices and then inserted into our pricing formula to get expected recovery rates under Moody's assumptions. The expected recoveries are then subtracted from ours to measure discrepancies between the two methodologies.

Figure 3 depicts the difference between the two calculations for residential properties. Both methods give similar expected recoveries for northern regions. For Friuli Venezia Giulia, Lombardia, Emilia Romagna, and Trentino Alto Adige, the percentage difference for residential (commercial) properties is 0.51% (1.35%), 2.90% (2.74%), 3.12% (3.47%), and 3.26% (0.97%), respectively. Although differences are large for residential properties in Molise (27.44%), Lazio (17.18%), Sicilia (15.13%), and Sardegna (14.50%). For commercial properties, the situation is quite similar with differences of 32.80%, 14.02%, 16.11%, and 14.11%, respectively.

Our estimates of expected recoveries, which are derived from an EOU process, range between 34.53% and 66.70%, with an average recovery of 54.48%. Moody's, which are obtained using the geometric Brownian motion, range from 53.44% to 74.90%, with an average of 64.03%. Interestingly, the lowest regional recovery rate obtained using Moody's practice is only slightly smaller than the average recovery rate obtained with our pricing approach.

The average recovery rates estimated in our model are broadly in line with findings in Ciocchetta et al. (2017) and Fischetto et al. (2018). This suggests that Moody's predictions on recovery rates are upward biased, and that Moody's underestimates the expected loss given default, especially with regards to less developed regions in Italy which exhibit high volatility.

By neglecting the actual risks affecting the market at regional and provincial levels, market practitioners might fail to address higher-than-expected loss given defaults. This can result in banks' inability to correctly quantify the riskiness of the assets held on their balance sheets. By estimating lower expected loss rates, banks fail to keep enough provisions for NPLs and would therefore not be sufficiently capitalized, violating Basel III recommendations.
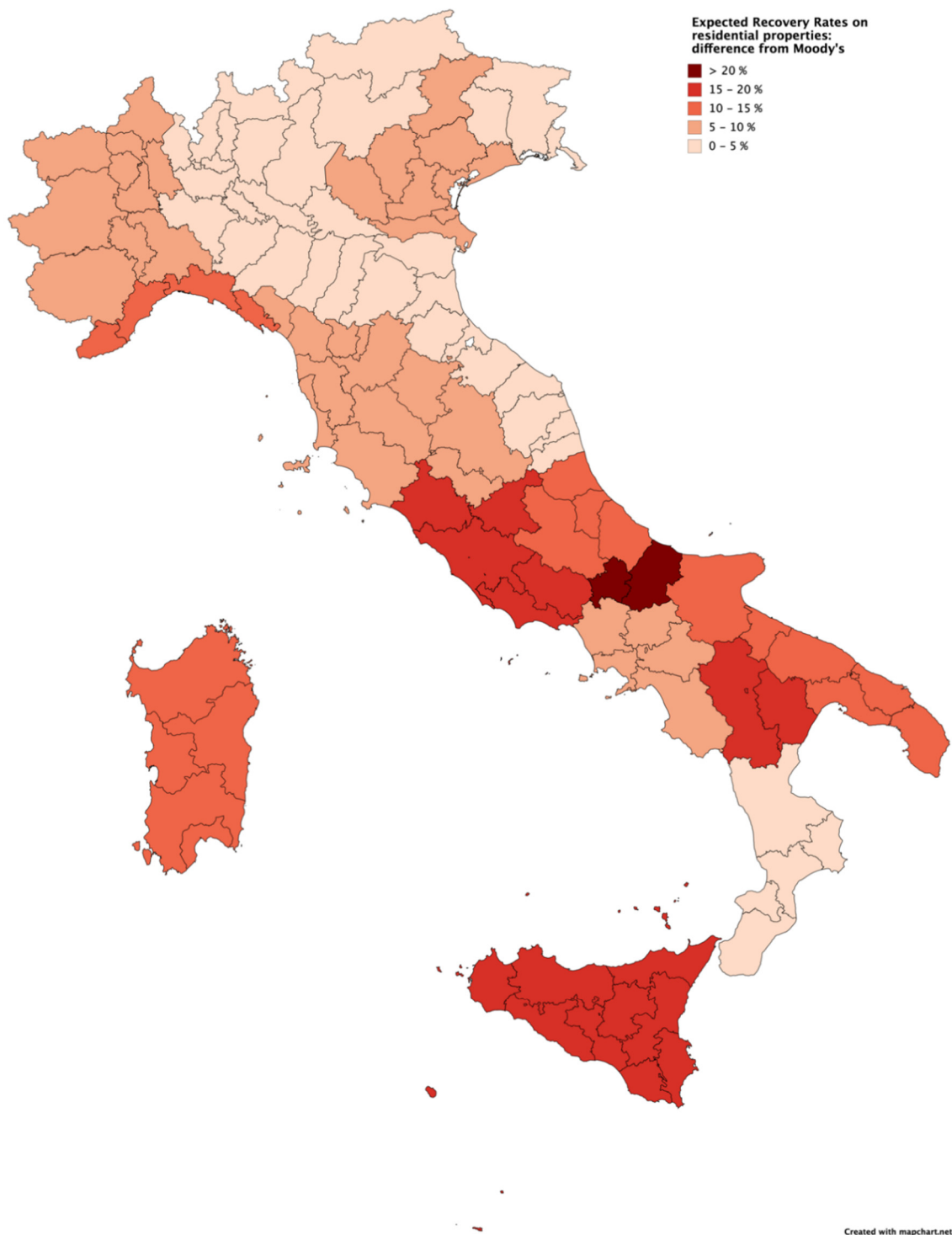
Figure 3. Expected recovery rates on residential properties: difference between Moody's and our estimates. (Mapchart.Net 2020).

4. Conclusions

Managing credit risk means knowing in advance how changes in the input parameters affect the estimation results. This enables adequate regulatory capital calculation, adequate economic capital calculation, adequate downturn-LGD (loss given default) estimation, and differentiated risk allocation due to risk-sensitive pricing. For existing defaulted loans, the knowledge about the effects of liquidation efficiency (courts timings) and cost factors on the LGD may have consequences for liquidation policy.

In this paper we focus on loans of the retail sector that are collateralized by residential and commercial real estate property in Italy. We find significant intra-regional differences in the Italian real estate market. When working with regional rather than provincial data, such differences are overlooked. At the regional level our results are much less optimistic than those derived using Moody's methodology. This implies that Italian banks might hold too little capital to cover expected losses from these engagements.

Although this study captures the most relevant characteristics of the two main property types (residential and commercial properties classified as being in normal condition), it would be of interest to develop this study further by using a larger panel data set including property location and property maintenance conditions. Further research should also add validation using actual liquidation data and compare these with forecasts derived in this paper, although the Bank of Italy report by Ciocchetta et al. (2017) highlights the "scarcity of reliable public data on banks' track record in bad loan recovery".

Author Contributions: Formal analysis, visualization, original draft preparation: M.P.; review and editing, supervision: K.R.S.-H. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

Accornero, Matteo, Piergiorgio Alessandri, Luisa Carpinelli, and Alberto Maria Sorrentino. 2017. *Non-Performing Loans and the Supply of Bank Credit: Evidence from Italy*. Rome: Bank of Italy, Questioni di Economia e Finanza.

Blanco, Roberto, and Ricardo Gimeno. 2012. Determinants of Default Ratios in the Segment of Loans to Households in Spain. 2012. Banco de Espana Working Paper No. 1210. Available online: https://ssrn.com/abstract=2007059 (accessed on 15 June 2019).

Chaiyapo, Nattiyaa, and Nattakorn Phewchean. 2017. An application of Ornstein-Uhlenbeck process to commodity pricing in Thailand. *Advances in Difference Equations: Springer Open Journal* 2017: 179. [CrossRef]

Ciocchetta, Federica, Francesco Maria Conti, Romina De Luca, Igino Guida, Anna Rendina, and Giovanni Santini. 2017. *Bad Loan Recovery Rates*. Rome: Bank of Italy, Notes on Financial Stability and Supervision, No. 7.

European Banking Authority. 2016. *EBA Report on the Dynamics and Drivers of Non-Performing Exposures in the EU Banking Sector*. London: European Banking Authority (EBA).

European Systemic Risk Board. 2017a. *Annual Report 2017*. Frankfurt: European Systemic Risk Board (ESRB), European System of Financial Supervision.

European Systemic Risk Board. 2017b. *Resolving Non-Performing Loans in Europe*. Frankfurt: European Systemic Risk Board (ESRB), European System of Financial Supervision.

Fabozzi, Frank J., Robert J. Shiller, and Radu S. Tunaru. 2010. Property Derivatives for Managing European Real-Estate Risk. *European Financial Management* 16: 8–26. [CrossRef]

Fabozzi, Frank J., Robert J. Shiller, and Radu S. Tunaru. 2012. A Pricing Framework for Real Estate Derivatives. *European Financial Management* 18: 762–89. [CrossRef]

Ferretti, Camilla, Giampaolo Gabbi, Piero Ganugi, Federica Sist, and Pietro Vozzella. 2019. Credit risk migration and economic cycles. *Risks* 7: 109. [CrossRef]

Fischetto, Antonio Luigi, Igino Guida, Anna Rendina, Giovanni Santini, and Marco Scotto di Carlo. 2018. *Bad Loan Recovery Rates in 2017*. Rome: Bank of Italy, Notes on Financial Stability and Supervision, No. 13.

Frontczak, Robert, and Stefan Rostek. 2015. Modeling loss given default with stochastic collateral. *Economic Modelling* 44: 162–70. [CrossRef]

Gao, Andre, Zhenguo Lin, and Carrie Fangzhou Na. 2009. Housing market dynamics: Evidence of mean reversion and downward rigidity. *Journal of Housing Economics* 18: 256–66. [CrossRef]

Giacomelli, Silvia, Tommaso Orlando, and Giacomo Rodano. 2018. *Real Estate Foreclosures: How the Process Works and the Effect of Recent Reforms*. Occasional papers, No. 448. Rome: Bank of Italy.

Iacus, Stefano M. 2008. *Simulation and Inference for Stochastic Differential Equations: With R Examples*. Milan: Springer Series in Statistics.

Kuchuk-Iatsenko, Sergii, and Yuliya Mishura. 2015. Option pricing in the model with stochastic volatility driven by Ornstein–Uhlenbeck process. Simulation. *Modern Stochastics: Theory and Applications* 2: 355–69. [CrossRef]

Leow, Mindy, and Christophe Mues. 2012. Predicting loss given default (LGD) for residential mortgage loans: A two-stage model and empirical evidence for UK bank data. *International Journal of Forecasting* 28: 183–95. [CrossRef]

Magri, Silvia, and Raffaella Pico. 2011. The rise of risk-based pricing of mortgage interest rates in Italy. *Journal of Banking & Finance* 35: 1277–90.

Mapchart.Net. 2020. Available online: https://mapchart.net/italy.html (accessed on 11 January 2020).

Mayer, Christopher J., Karen M. Pence, and Shane M. Sherlund. 2009. The rise in mortgage defaults. *Journal of Economic Perspectives* 23: 27–50. [CrossRef]

Mejia Vega, Carlos Armando. 2018. Calibration of the exponential Ornstein-Uhlenbeck process when spot prices are visible through the maximum log-likelihood method. Example with gold prices. *Advances in Difference Equations* 2018: 269. [CrossRef]

Merton, Robert C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance* 29: 449–70.

Moody's Investors Service. 2004. *Moody's Approach to Rating Italian RMBS*. New York: Moody's Investors Service, International Structured Finance.

Moody's Investors Service. 2019. *Moody's Approach to Rating Securitizations Backed by Non-Performing and Re-Performing Loans*. New York: Moody's Investors Service.

Perelló, Josep, Ronnie Sircar, and Jaume Masoliver. 2008. Option pricing under stochastic volatility: the exponential Ornstein–Uhlenbeck model. *Journal of Statistical Mechanics: Theory and Experiment* 6: 1–22. [CrossRef]

Qi, Min, and Xinlei Zhao. 2011. Comparison of modeling methods for loss given default. *Journal of Banking & Finance* 35: 2842–55.

Van Damme, Gert. 2011. A generic framework for stochastic loss-given-default. *Journal of Computational and Applied Mathematics* 235: 2523–50. [CrossRef]

Ye, Hui, and Anthony Bellotti. 2019. Modelling recovery rates for non-performing loans. *Risks* 7: 19. [CrossRef]