

Money Laundering in the Real Estate sector: evidence from the Italian market at a provincial level

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Talk overview

- Introductory remarks
- Theoretical characteristics
- Variables' issues
- Implementation of the model and main results
- Conclusions

Facts about Real Estate and Unobservable Economy in Italy

Reasons behind this choice:

- relevance of the real estate sector
- dimension of criminal/shadow economy and money laundering
(see *Ardizzi et al., 2014*)

Presence of Crime in the Real Estate literature

Micro literature:

- *Diaz-Serrano* (2005)
- *Kiel and Zabel* (2008)
- *Stadelmann* (2010)
- *Kiefer* (2011)

Macro literature:

- *Potepan* (1996)
- *Scafidi et al.* (1998)
- *Schneider* (2004)
- *Yan et al.* (2007)

The Model

Errors peculiarities:

- time autocorrelation (Prais-Winsten)
- heteroscedasticity (PCSE)
- spatial correlation (PCSE)

Dataset construction

Hypotheses about the determinants of real estate market prices:

- per capita wages: *pil_pc*
- population distribution: *pop_25*
- wealth distribution: *u*
- rents (and their determinants): *aff*
- cost of capital: *INT*
- market efficiency: *IMI*
- supply regulation: *stock_pop*
- hedonic aspects: *verde_pc*, *tras_pc* and *rdiff*
- crimes connected to ML: ***ENTERPRISE*** and ***POWER***
- probability of being prosecuted for ML: *sos_pop*
- tax evasion: *evas_comm* and *evas_impr*

Complete Regression

$$\begin{aligned} \text{Pimm}_{it} = & \alpha_0 + \alpha_1 \text{pil_pc}_{it} + \alpha_2 \text{pop_25}_{it} + \alpha_3 \text{u}_{it} + \\ & + \alpha_4 \text{aff}_{it} + \alpha_5 \text{INT}_{it} + \alpha_6 \text{IMI}_{it} + \alpha_7 \text{stock_pop}_{it} + \\ & + \alpha_8 \text{verde_pc}_{it} + \alpha_9 \text{tras_pc}_{it} + \alpha_{10} \text{rdiff}_{it} + \\ & + \alpha_{11} \text{ENTERPRISE}_{it} + \alpha_{12} \text{POWER}_{it} + \alpha_{13} \text{sos_pop}_{it} + \\ & + \alpha_{14} \text{evas_comm}_{it} + \alpha_{15} \text{evas_impr}_{it} + \varepsilon_{it} \end{aligned}$$

Starting Regressions

<i>regressor</i>	<i>Model 1</i>		<i>Model 2</i>		<i>Model 4</i>	
<i>pil_pc</i>	4.368	**	0.951		2.001	
<i>pop_25</i>	1630.781	***	1975.031	***	2184.802	***
<i>u</i>	119.170		118.543		-379.681	
<i>aff</i>	18.391	***	17.765	***	16.792	***
<i>INT</i>	-4.620		0.639		-17.596	
<i>IMI</i>	-4759.76	**	-5008.203	**	-5783.491	**
<i>stock_pop</i>	866.916	***	687.330	***	670.346	***
<i>verde_pc</i>	-		0.086	***	0.084	***
<i>tras_pc</i>	-		0.393	***	0.299	**
<i>rdiff</i>	-		0.583		1.133	**
<i>ENTERPRISE</i>	-		-		207.825	***
<i>POWER</i>	-		-		12.479	
<i>sos_pop</i>	-		-		36.915	
<i>evas_comm</i>	-		-		-50.503	**
<i>evas_impr</i>	-		-		-4.837	
<i>constant</i>	-1441.960	***	-1549.069	***	-1798.419	***

Baseline model - Coefficients

<i>regressor</i>	<i>coefficient</i>	<i>z value</i>	
<i>pil_pc</i>	2.307	(0.83)	
<i>pop_25</i>	2321.452	(4.30)	***
<i>aff</i>	16.894	(35.64)	***
<i>IMI</i>	-5023.302	(-2.95)	***
<i>stock_pop</i>	658.431	(5.07)	***
<i>verde_pc</i>	0.083	(4.76)	***
<i>tras_pc</i>	0.327	(2.60)	***
<i>rdiff</i>	1.155	(1.96)	**
<i>ENTERPRISE</i>	189.081	(3.97)	***
<i>POWER</i>	11.641	(0.80)	
<i>evas_comm</i>	-59.152	(-2.18)	**
<i>evas_impr</i>	-3.480	(-0.49)	
<i>constant</i>	-1951.982	(-4.31)	***

Baseline model - Percentage contribution of the variables

	<i>Italy</i>	<i>north</i>	<i>centre</i>	<i>south</i>
<i>pimm</i>	100	100	100	100
Positive contribution				
<i>pop_25</i>	154.89	142.45	135.17	204.45
<i>aff</i>	72.05	68.47	74.81	75.82
<i>stock_pop</i>	30.51	28.55	24.98	41.31
<i>ENTERPRISE</i>	13.90	11.01	11.65	22.52
<i>pil_pc</i>	5.05	5.54	4.48	4.77
<i>rdiff</i>	2.69	3.68	2.03	1.50
<i>tras_pc</i>	2.04	2.20	1.74	2.08
<i>POWER</i>	1.31	0.58	0.80	3.41
<i>verde_pc</i>	1.01	0.96	1.04	1.06
Negative contribution				
<i>constant</i>	-170.12	-151.28	-145.46	-238.73
<i>IMI</i>	-11.48	-11.16	-9.88	-14.11
<i>evas_comm</i>	-1.43	-0.73	-0.99	-3.37
<i>evas_impr</i>	-0.40	-0.27	-0.36	-0.72

Disaggregated model - Coefficients

Model 5 (disaggregated)

<i>regressor</i>	<i>coefficient</i>	<i>z value</i>	
<i>pil_pc</i>	3.547	(1.22)	
<i>pop_25</i>	2192.742	(4.76)	***
<i>aff</i>	16.413	(37.96)	***
<i>IMI</i>	-4625.375	(-2.80)	***
<i>stock_pop</i>	669.045	(5.50)	***
<i>verde_pc</i>	0.082	(5.09)	***
<i>tras_pc</i>	0.352	(2.58)	***
<i>rdiff</i>	1.246	(2.01)	**
<i>ENT_a</i>	66.664	(2.67)	***
<i>ENT_b</i>	146.367	(3.78)	***
<i>POWER</i>	7.183	(0.56)	
<i>evas_comm</i>	-70.817	(-2.54)	**
<i>evas_impr</i>	-10.893	(-1.58)	
<i>constant</i>	-1892.47	(-4.80)	***

Model 5 (baseline)

<i>regressor</i>	<i>coefficient</i>	<i>z value</i>	
<i>pil_pc</i>	2.307	(0.83)	
<i>pop_25</i>	2321.452	(4.30)	***
<i>aff</i>	16.894	(35.64)	***
<i>IMI</i>	-5023.302	(-2.95)	***
<i>stock_pop</i>	658.431	(5.07)	***
<i>verde_pc</i>	0.083	(4.76)	***
<i>tras_pc</i>	0.327	(2.60)	***
<i>rdiff</i>	1.155	(1.96)	**
<i>ENT</i>	189.081	(3.97)	***
<i>POWER</i>	11.641	(0.80)	
<i>evas_comm</i>	-59.152	(-2.18)	**
<i>evas_impr</i>	-3.480	(-0.49)	
<i>constant</i>	-1951.982	(-4.31)	***

Disaggregated model - Percentage contribution of the variables

	<i>Italy</i>	<i>north</i>	<i>centre</i>	<i>south</i>
<i>pimm</i>	100	100	100	100
Positive contribution				
<i>pop_25</i>	146.13	134.49	127.62	193.43
<i>aff</i>	70.03	66.50	72.65	73.78
<i>stock_pop</i>	30.94	29.00	25.38	42.05
<i>ENTERPRISE_b</i>	10.63	8.51	8.90	17.26
<i>pil_pc</i>	7.76	8.51	6.88	7.35
<i>ENTERPRISE_a</i>	5.81	3.93	5.37	10.23
<i>rdiff</i>	2.91	3.97	2.19	1.62
<i>tras_pc</i>	2.19	2.36	1.87	2.25
<i>verde_pc</i>	1.00	0.95	1.04	1.06
<i>POWER</i>	0.80	0.36	0.49	2.10
Negative contribution				
<i>constant</i>	-164.71	-146.61	-140.97	-231.84
<i>IMI</i>	-10.57	-10.27	-9.10	-13.01
<i>evas_comm</i>	-1.70	-0.88	-1.19	-4.04
<i>evas_impr</i>	-1.24	-0.83	-1.14	-2.25

Simulations - northern Italy

<i>province</i>	<i>quotation</i>	<i>theoretical value</i>	<i>difference</i>	<i>difference %</i>
<i>Rimini</i>	2290.39	1951.50	-338.89	-14.80%
<i>Genova</i>	2290.15	1964.90	-325.25	-14.20%
<i>Savona</i>	2600.82	2301.91	-298.91	-11.49%
<i>Bologna</i>	2445.12	2152.63	-292.50	-11.96%
<i>Imperia</i>	2070.42	1783.57	-286.85	-13.85%
<i>Ravenna</i>	1501.35	1264.53	-236.82	-15.77%
<i>Torino</i>	1670.69	1447.31	-223.38	-13.37%
<i>Milano</i>	2063.36	1843.77	-219.59	-10.64%
<i>Parma</i>	1726.33	1531.50	-194.83	-11.29%
<i>Padova</i>	1207.95	1021.61	-186.34	-15.43%
<i>Rovigo</i>	927.92	814.31	-113.61	-12.24%
<i>Cremona</i>	947.22	835.71	-111.51	-11.77%
<i>Cuneo</i>	1192.45	1082.31	-110.14	-9.24%
<i>Udine</i>	918.93	820.47	-98.46	-10.71%
<i>Treviso</i>	1282.79	1184.82	-97.97	-7.64%
<i>Mantova</i>	1091.94	994.97	-96.97	-8.88%
<i>Pordenone</i>	969.70	877.38	-92.32	-9.52%
<i>Lecco</i>	1434.42	1342.67	-91.74	-6.40%
<i>Biella</i>	822.88	737.58	-85.30	-10.37%
<i>Sondrio</i>	1140.44	1055.72	-84.72	-7.43%

Simulations - central Italy

<i>province</i>	<i>quotation</i>	<i>theoretical value</i>	<i>difference</i>	<i>difference %</i>
<i>Lucca</i>	2099.46	1817.07	-282.39	-13.45%
<i>Pistoia</i>	1664.95	1414.35	-250.59	-15.05%
<i>Massa</i>	1814.19	1567.20	-247.00	-13.61%
<i>Pescara</i>	966.65	728.21	-238.44	-24.67%
<i>Firenze</i>	2653.18	2416.38	-236.80	-8.93%
<i>Livorno</i>	2330.46	2100.14	-230.32	-9.88%
<i>Roma</i>	2893.34	2664.50	-228.85	-7.91%
<i>L'Aquila</i>	901.71	694.70	-207.01	-22.96%
<i>Teramo</i>	904.30	698.94	-205.36	-22.71%
<i>Latina</i>	1398.89	1197.28	-201.61	-14.41%
<i>Pisa</i>	1473.80	1306.13	-167.67	-11.38%
<i>Viterbo</i>	1070.55	904.21	-166.34	-15.54%
<i>Pesaro</i>	1233.45	1068.49	-164.96	-13.37%
<i>Terni</i>	1002.84	849.49	-153.36	-15.29%
<i>Ancona</i>	1489.97	1339.46	-150.50	-10.10%
<i>Arezzo</i>	1317.35	1169.82	-147.53	-11.20%
<i>Chieti</i>	1011.99	871.04	-140.95	-13.93%
<i>Macerata</i>	1260.73	1122.28	-138.44	-10.98%
<i>Frosinone</i>	887.97	763.30	-124.67	-14.04%
<i>Siena</i>	2258.58	2142.25	-116.33	-5.15%

Simulations - southern Italy

<i>province</i>	<i>quotation</i>	<i>theoretical value</i>	<i>difference</i>	<i>difference %</i>
<i>Napoli</i>	1811.02	1291.39	-519.63	-28.69%
<i>Caserta</i>	1077.96	662.22	-415.75	-38.57%
<i>Catania</i>	1040.04	685.38	-354.66	-34.10%
<i>Palermo</i>	1226.76	885.86	-340.90	-27.79%
<i>Trapani</i>	691.78	443.14	-248.64	-35.94%
<i>Reggio Calabria</i>	668.05	429.04	-239.01	-35.78%
<i>Brindisi</i>	781.43	543.24	-238.19	-30.48%
<i>Salerno</i>	1385.60	1151.57	-234.03	-16.89%
<i>Catanzaro</i>	727.82	501.43	-226.39	-31.10%
<i>Siracusa</i>	665.62	446.55	-219.07	-32.91%
<i>Lecce</i>	759.78	553.74	-206.04	-27.12%
<i>Messina</i>	806.46	603.75	-202.71	-25.14%
<i>Taranto</i>	726.82	526.08	-200.74	-27.62%
<i>Ragusa</i>	766.16	567.98	-198.18	-25.87%
<i>Agrigento</i>	653.00	459.91	-193.09	-29.57%
<i>Cosenza</i>	580.46	404.29	-176.17	-30.35%
<i>Benevento</i>	828.58	671.68	-156.89	-18.94%
<i>Avellino</i>	790.36	654.55	-135.81	-17.18%
<i>Campobasso</i>	816.89	714.46	-102.43	-12.54%

Conclusions

- relevance of ENTERPRISE
- macro-areas comparisons
- effects on real economy
- effects on equity

Limits

- number of analyzed provinces
- aggregation data procedures
- county town variables
- space and time restrictions in ML
- connection between crimes and related profits
- weight of crimes
- proportion between observed/occurred crimes

Further improvements

- quantification of the capitals laundered through real estate
- extension of the time series up to recent years
- application of the procedure to other goods