Preventing the deterioration of bank loan portfolio quality: a focus on unlikely-to-pay loans

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Abstract

Using a novel panel data-set, covering the period 2010-2016, the study detects determinants of: a) new flows of unlikely-to-pay loans (UTP), comparing them to determinants of bad loans; b) out-flows from UTP to performing and bad loans. Lending policy, bank capital, bad management, and procyclical credit policy hypotheses are tested. Determinants verified by the literature on non-performing loans are in part confirmed for UTP and in part rejected. The main findings show: i) a positive relationship between bank capital and the new flows of both UTP and bad loans; ii) reducing cost efficiency increases new flows of UTP and the worsening of UTP towards bad loans; iii) having a specific office/unit to manage impaired loans increases flows from UTP to performing loans, but does not decrease flows to bad loans. Our study is useful for banks in order to prevent new impaired exposures, to accelerate the transition from UTP to performing loans, and prevent their worsening to bad loans. Findings reveal the importance of a sound and proactive UTP management, given the need for banks to increase provisions for covering UTP in the near future.

JEL Code: G21; C23

Keywords: unlikely-to-pay loans; non-performing loans; banks; Italian banking system; credit risk management; dynamic panels

1. Introduction

It is widely recognized that a high level of non-performing loans (hereafter NPL) affects bank lending capacity, lowers bank profitability, and affects ability to raise new capital (BCE, 2017; European Parliament, 2018). A high level of NPL can also alter market perceptions of the banking sector as a whole (European Council, 2017). Consequently, studying NPL determinants has become an important goals for authorities and researchers.

According to their level of deterioration, NPL can be distinguished into three categories: bad loans, unlikely to pay loans (hereafter UTP), and past due[i]. Banks are expected to increase the level of provisioning and to apply further capital deductions related to UTP in the near future, as a result of accounting and regulatory reforms, such as the introduction of new accounting standards (European Commission, 2016), a new definition of default (EBA, 2016), the guidelines to banks on NPL (ECB, 2017; ECB, 2018), and Calendar Provisioning for non-performing exposures (European Parliament, 2019).

Preventing UTP and encouraging the transition from UTP to performing loans is fundamental for reducing capital requirements and loss coverage requirements. Our study investigates the determinants of this specific category of NPL, and the impact of bank specific variables on the onset of new UTP flows. It also verifies the determinants of the annual decreases of UTP exposures, deepening the analysis on the flows of UTP which return *in bonis* or which move to bad loans. This allows us to investigate both improvement and worsening in credit portfolio quality. The study also verifies the determinants of new flows of bad loans. They have a higher level of deterioration than UTP and they are used in our research as a basis for comparison between non-performing exposures[ii].

We believe that UTP exposures should be analyzed separately from other categories of NPL for two main reasons: a) The average expected rate of losses and the current level of provisions are extremely different for each class of loan; b) Unlike European bad loan markets, the UTP market is relatively new, and is limited in terms of volumes and number of transactions (see Appendix A for further details).

The study focuses on the Italian banking system for the seven years 2010-2016. This period includes the whole Sovereign debt crisis in Europe and the subsequent economic recovery, when the level of NPL increased dramatically. We investigate the case study of Italy because, excluding the three countries which received financial assistance from the EU (Greece, Cyprus, and Portugal), Italy has the highest NPL ratio in the EU, so NPL management in this country is particularly significant (Baldini and Causi, 2019). Further details of the Italian NPL market are reported in Appendix A.

Our main findings show a positive relationship between bank capital and the new flows of both UTP and bad loans. Besides, the lower bank efficiency, the higher the new flows of UTP and the flows of UTP that become bad loans: a high cost income ratio is related with high impaired loans and a progressive worsening of credit quality. Nevertheless, analyzing out-flows from UTP towards performing loans and bad loans separately, the study verifies that dedicated and proactive organization helps banks to increase the flow from UTP to performing loans. Unlike credit deterioration, the transition of impaired positions towards *in bonis* portfolio does not show a significant relationship with cost efficiency, but it is sensitive to investments in a specialized structure for a sound NPL management.

Our contribution to the existing literature is three-fold.

First, our study focuses on the determinants of UTP, whereas previous literature usually analyses more in general the NPL portfolio, without considering different categories of impaired loans. While some authors studied the determinants of bad loans (Marcucci and Quagliariello, 2009; Bofondi and Ropele, 2011; Baldini and Causi, 2019), to the best of our knowledge there are no studies on the determinants of UTP.

This paper also presents a dynamic study, based on data about new flows of impaired loans. Previous literature on NPL determinants has frequently used the stock level of NPL at the end of the year (using the NPL ratio). This ratio can vary over time thanks to new flows of impaired positions deriving from the deterioration of performing loans, write-offs, sales, and thanks to transitions to performing exposures. Identifying the determinants of impaired loans using only the NPL ratio offers

a partial view of the whole phenomenon; it considers deterioration and the improvement of the NPL loans without explaining why the ratio has increased or decreased at the end of the year. Literature studying changes over time in this ratio (Louzis et al., 2012), also focuses on the effects of improvement or worsening in the degree of deterioration. Our dataset on new flows of UTP and bad loans does not consider write-offs, sales or returns *in bonis*, but focuses on the real gross increase in impaired exposures. This allows us to verify the actual determinants of new UTP and bad loans. We also test the determinants of out-flows from UTP, still studying the flows of UTP returning *in bonis* separately from those worsening to become bad loans. Compared to other research that analyzes the determinants of new flows of NPL (Bofondi and Gobbi, 2004; Quagliariello, 2008; Marcucci and Quagliariello, 2009; Bofondi and Ropele, 2011), we focus on the UTP portfolio and add the analysis of out-flows from UTP to other classes of loan. To the best of our knowledge, no other study extends the analysis of the out-flows from NPL to performing loans or to specific categories of impaired loans. Focusing on the in-flows to, and the out-flows from, a loan portfolio characterized by an intermediate level of deterioration allows us to verify the underlying reasons for the evolution of credit quality, and raises important implications for management.

In particular, to verify the effects of managerial choices, we test the impact of the introduction of organizational units/offices dedicated to the management and recovery of impaired loans. We analyze this factor as a potential determinant of the transition from non-performing to performing loan, as well as between different categories of NPL. This is further contribution of our research to the literature on the topic.

The rest of the paper is structured as follows. Section 2 provides a brief literature review on the determinants of NPL. Section 3 describes the sample and the data. Section 4 describes the methodology. Results are reported in Section 5 and robustness tests and additional analyses in Section 6. Lastly, conclusions and policy implications are described in Section 7.

2. Literature review and hypotheses

NPL are one of the biggest obstacles to the development of the banking sector and the bank credit market, and have been increasingly studied by researchers and authorities in recent years (see e.g. Hou and Dickinson, 2007; Panetta, 2013; Baldini and Causi, 2019).

Regarding the determinants of NPL, two different strands can be distinguished in the literature: i) studies on the macro-economic factors influencing NPL; ii) studies on the bank specific determinants of NPL.

Concerning the macro-economic factors influencing NPL, many authors underline the close relationship between the economic cycle and the credit portfolio quality of banks (Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Boudriga et al., 2009; Bofondi and Ropele, 2011; Glen and Mondragon-Velèz, 2011; Beck et al., 2013; Castro, 2013; Grigoli et al., 2018; Olszak, 2018; Chavan and Gambacorta, 2019). To sum up these studies, negative changes in macroeconomic conditions play a crucial role in the worsening of the loan portfolio quality, pushing banks to increase loan loss provisions, and raising the level of NPL ratio.

The second strand of literature, focused on bank specific determinants of NPL, includes three important fields of studies, concerning: a) bank lending policy; b) bank capitalization; and c) bank economic performance (efficiency and profitability). Our study is focused on this second strand of literature. We refer to all the main hypotheses tested by the literature on NPL, in order to verify whether they are confirmed or rejected for the specific category of UTP, and, for comparison, for the class of bad loans.

Concerning bank lending policy, there are several contributions in the literature about the relationships between credit growth and loan portfolio quality, both before the crisis (Sinkey and Greenwalt, 1991; Keeton, 1999; Radlet and Sachs, 1998; Ranjan and Dhal, 2003; Dell'Arriccia and Marquez, 2006; Jimenez and Saurina, 2006), and in the ensuing period of financial turmoil (Foos, 2010, Amador et al., 2013; Baselga-Pascual et al., 2015; Vithessonthi, 2016). In particular, Vithessonthi (2016), analyzing 85 public commercial Japanese banks during the period 1993-2013

and using both OLS and two-step GMM regressions, finds evidence that bank credit growth is positively correlated to NPL just before the crisis, and negatively correlated after the financial turmoil. This illustrates the time-varying nature of the impact of credit growth on NPL, and suggests that financial crisis alters the relationship between the two variables. The financial crisis appears to modify the mechanisms through which bank lending impacts NPL. As stated by Jimenez and Saurina (2006), during a positive business cycle, banks that increase their lending activity tend to lower their credit standards, and accept a poorer quality of borrowers. Although credit grows and bank profitability increases during the positive cycle, the lowering in credit standards causes an increase in impaired loans during the subsequent downturn period. The close relationship between the business cycle and loan standards is identified by several authors (Berger and Udell, 2004; Dell'Arriccia and Marquez, 2006). Their results suggest that standards applied by banks vary over the cycle, as well as across financial institutions (Cucinelli et al., 2018).

Since the period observed in our analysis runs from 2010 to 2016, and covers the entire Sovereign financial crisis, we test the bank lending policy hypothesis for specific categories of impaired loans:

Hypothesis 1: A more aggressive lending policy is positively associated with increases in flows from performing loans to both UTP and bad loans.

With regard to bank capitalization, several studies investigate whether bank leverage can affect the level of NPL in credit portfolios, given the incentive to take more or less risk in relationship to the capital strength of bank. The effect of the level of capitalization on loan losses is ambiguous. Some authors, in particular studying the period pre-Basel II, tested the so-called moral hazard hypothesis: at lower level of bank capital, the problem of moral hazard behaviour of bank managers may arise, leading to future increases in NPL (Keeton and Morris, 1987; Berger and DeYoung, 1997; Jimenez and Saurina, 2006; Podpiera and Weill, 2008; Louzis et al., 2012; Klein, 2013; Makri et al., 2014; Chaibi, 2016). In line with this hypothesis, a negative relationship has been noted between bank

capitalization and NPL. However, to reduce this incentive, during recent years, regulators have imposed higher risk-sensitive capital requirements (Basel Accord II and III), so that only well-capitalized banks can satisfy their appetite for high risk and consequently have a high risk profile. Besides, managers in highly capitalized banks have to look for higher returns on assets, in order to compensate their shareholders for the higher riskiness of their investment, which leads to a positive relationship between capital and NPL (Barth et al., 2004; Macit 2012; Cucinelli, 2018). This is consistent with the results of Godlewski (2005), Boudriga et al. (2009), and Ghosh (2015): through engaging in more risky activities, banks with higher solvency level experience higher NPL. In light of this literature and the new regulatory framework, we expect the more capitalized banks are those with lower credit portfolio quality. We test this hypothesis for specific categories of impaired loans:

Hypothesis 2: High regulatory capital is positively associated with increases in flows from performing loans to both UTP and bad loans.

Other authors investigate different hypotheses related to operating costs and profitability, to study the role of bank performance in determining the quality of credit portfolios. Concerning the level of costs borne by banks, the literature studies two contrasting hypotheses: skimping and bad management (Berger and De Young, 1997; Williams, 2004; Rossi, Schwaiger and Morris, 2005; Podpiera and Weill, 2008; Espinoza and Prasad, 2010; Louzis et al., 2012; Gosh, 2015; Chaibi, 2016; Cucinelli et al., 2018; Ozili, 2019). According to the first hypothesis, lower levels of operating costs may reflect a cost cutting policy, and, consequently, a decrease in the resources allocated to selecting and monitoring lending. Managers reduce short-term operating costs, decreasing the quality of screening and monitoring activities, leading in the long run to an increase in impaired loans. The hypothesis of skimping posits a negative relationship between the level of operating costs and NPL. According to the hypothesis of bad management, a higher level of costs to income ratio is an index of inefficiency and a sign of poor management. In the field of credit risk, bad management is related

to a lack of skills in evaluating counterparties' creditworthiness, assessing the value of collateral, and monitoring borrowers. Poor skills in credit management can produce an increase in NPL. The bad management hypothesis states that there is a negative relationship between cost efficiency and NPL, explained by the link between unqualified managers and poor skills in credit risk management. Although the literature tests both hypotheses, results show that in general the hypothesis of bad management explains the relationship between cost efficiency and the evolution of NPL more successfully than the hypothesis of skimping (Berger and De Young, 1997; Podpiera and Weill, 2008; Espinoza and Prasad, 2010; Louzis et al., 2012; Gosh 2015; Chaibi, 2016). As a consequence, we test the bad management hypothesis for different categories of impaired loans:

Hypothesis 3a: Low cost efficiency is positively associated with increases in flows from performing to both UTP and bad loans.

Analyzing profitability, the hypothesis of procyclical credit policy was introduced by Rajan (1994). In his model, credit policy is determined by both the maximization of bank earnings and the concerns of bank managers about short-term reputation. In line with this, management may manipulate current earnings by resorting to a liberal credit policy. In an attempt to persuade the market, this policy increases current earnings, moving the risk into the future. In addition, a bank may also use loan loss provisions in order to boost its current profitability. Because of this, past earnings may be positively associated with future NPL (Poghosyan and Cihak, 2011; Louzis et al., 2012; Abid et al., 2014).

In line with the literature about NPL, we test whether the procyclical credit policy hypothesis relating to bank performance is confirmed for UTP and bad loans:

Hypothesis 3b: High profitability is positively associated with increases in flows from performing loans to both UTP and bad loans.

Nevertheless, ratios like cost to income and ROAE reflect a wide range of costs and revenues, related to different managerial areas, and it is not possible to deduce from them effectively the real effort that a bank makes to ensure higher loan quality. In order to investigate this more closely, we verify the role of specific investments for improving the management of credit risk and the recovery of non-performing exposures. In particular, we study the impact of the presence of a business unit/office dedicated to NPL. This is a specialized structure responsible for the entire monitoring and recovery process of NPL positions, able to intervene on the basis of policies defined for specific segments of impaired exposures or individual positions. Specifically, we aim to verify the impact of this unit/office on the evolution of the UTP portfolio. Given that a reduction in the UTP exposures can occur when the credit merit of loans either improves or worsens, in order to test the impact of investments in organizational structures, we examine flows from UTP to performing loans separately from flows of UTP to bad loans.

Hypothesis 4: Banks with a dedicated and proactive unit/office for non-performing credit management and recovery show a higher flow of UTP to performing loans and a lower flow of UTP to bad loans.

3. Sample and data

Our initial sample comprised all Italian banks appearing in the SNL Unlimited database (419 banks)[iii]. After checking and skimming the data according to criteria reported below in this section, our final sample comprises 73 Italian banks. They represent 72% of bank total assets at the end of 2016 and about 98% of the total Italian UTP.

We include both listed and unlisted banks, as well as banks which closed down during the period observed (i.e. Banca Marche and Banca Etruria). We exclude very small banks, i.e. those with assets of less than 1 billion euros in 2016. These criteria halved our initial sample. A size threshold is

necessary in order to exclude those smaller banks which are not usually full-service institutions and which tend to have concentrated loan portfolios, as they can be vulnerable to sectoral or regional disturbance. Banks also need to have at least three sequential years of data. Moreover, because credit risk and the related capital policies are usually managed at group level in the case of banking groups, we consider the parent company and data at consolidated level. Only when the bank is under 50% owned by other banks do we consider unconsolidated balance sheet data (Cucinelli et al., 2018). From the initial 419 banks, this left 122 banks. Moreover, to analyze banks really focused on lending activity, in line with Bonaccorsi di Patti (2016)[iv], our sample includes only intermediaries that show a gross loans over total asset ratio higher than 50% in the last observed year. In fact, Ayadi et al. (2019) underline that among the five bank business models identified in their analysis, banks more oriented to retail activities[v] (i.e. banks with a retail and diversified business model that differ from wholesale and investment business model) show an average customer loans over total asset ratio ranging from 50.38% to 70.95%. Being more exposed to customer loans, these banks are most exposed to credit risk, as suggested by Ayadi et al. (2019). This highlights that banks with a retail and diversified business model show higher non-performing loans over gross loans ratio than banks more oriented to wholesale and investment activities. We hand-checked banks excluded from our initial sample using this threshold, and verified that excluded banks are actually more involved in activities other than lending. Furthermore, most of these banks would have been excluded anyway, because they do not lie within other parameters of sample definition. Some belonged to a banking group such as Fideuram, and others, such as some cooperative banks, are small institutions with less than 1 million euro of total assets. The final sample, based on these criteria, is made up of 102 banks. We collect data from banks' balance-sheets and find complete data on the composition of credit portfolio for 73 banks.

A unique database of UTP loans relating to the Italian banking system is constructed from different sources. UTP data are hand-collected from bank balance-sheet reports from 2010 to 2016, a particularly difficult period for the Italian banking system. Our sample period starts at the end of

2010, before Italy was hit by sovereign shocks that caused further financial market distress (Bofondi et al. 2017). The end date is December 2016: by that time the impact of the global and sovereign shocks had fully materialized (Accornero et al., 2017). During this period, the credit portfolio of Italian banks worsened: non-performing exposures rose from 157 billion euro in 2010 to 341 billion euro at the end of 2015. After 2015, stock declined constantly thanks to the improvement in economic conditions in Italy and the selling of NPL which banks started after 2015-2016 (Bank of Italy, 2018; PWC, 2019).

We collect yearly data referring to the stocks of UTP, the flows from performing loans to UTP and to bad loans, and the flows from UTP to bad loans and to performing loans[vi].

We also include bank-specific variables downloaded from the SNL Unlimited database.

4. Econometric methodology

The analysis uses an unbalanced panel of 73 Italian banks over a period of 7 years (2010-2016). We run panel data econometric regressions to detect first the determinants of UTP and bad loans (the flows from performing loans to UTP over gross loans and the flows from performing loans to bad loans over gross loans) and, secondly, the determinants of the out-flows from UTP to other NPL categories and to performing loans.

As underlined by the empirical literature on NPL, static estimators, mostly run with Fixed Effect (e.g. Podpiera and Weill, 2008; Foos et al., 2010; Klein, 2013), implicitly assume no significant persistence of the dependent variable across time. It is crucial to note that if the data generating process displays time persistence, fixed effect estimates will be biased and inconsistent, i.e. not reliable in the empirical analysis. For this reason, our analysis is performed by running a two-step GMM estimator method (Arellano and Bover, 1995; Blundell and Bond, 1998). In fact, the first difference GMM (Arellano and Bond, 1991) solves the endogeneity, heteroscedasticity and serial correlation problems in static panel data problem, but it is not efficient when the panel data is dynamic. The system GMM estimator is a system that contains both the levels and the first difference

equations. It provides an alternative to the standard first difference GMM estimator. Unlike static panel data models, dynamic panel data models include among regressors the lagged level of the dependent variable. Moreover, the use of the two-step system GMM method allows us to address the endogeneity problem arising from the risk of reverse causality in the econometric specification. To address this problem, in both our analyses, we adopt the two-step system GMM estimate and we construct instrument for the lagged dependent variable from the second and third lags of dependent variable in levels. We include the second lagged difference as an additional instrument. In fact, Arellano and Bover (1994) and Blundell and Bond (1998) emphasize that the lagged difference of the endogenous variables improves the precision of the GMM estimator when they are used as instruments for the variables in levels. We choose these instrumental variables, internal to our dataset, on the basis of lags of instrumented variables because the estimators do not assume that good instruments are available outside the immediate dataset (Roodman, 2009). We adopt robust standard errors, as recommended by Arellano and Bond (1991), because standard errors tend to be biased downward. Consequently, we use the Windmeijer bias-corrected (WC) robust VCE, which Windmeijer (2005) showed to work well. Furthermore, this model is designed for small-T and large-N panels.

To assess the stationarity of the dependent and independent variables, we perform the Choi Fisher-type (2001) test for unit root non-stationarity. This test is in line with specific characteristics of our unbalanced dataset, and strongly rejects the null hypothesis that all the panels contain unit roots for each dependent variable used.

We run the models on both the flow from performing loans to UTP over gross loans and the flow from performing loans to bad loans over gross loans. The aim is to assess whether the determinants of the new flows of UTP are the same as those observed in previous studies on bad loans (or more generally NPL).

The two-step system GMM model is the following:

$$\Delta In\_Flows_{i,t} = \beta_1 \Delta In\_Flows_{i,t-1} + \beta_2 \Delta TIER1_{i,t-1} + \beta_3 \Delta ROAE_{i,t-1} +$$

$$\beta_4 \Delta COST\_INCOME_{i,t-1} + \beta_5 \Delta GRGL_{i,t-1} + \beta_6 \Delta GL\_TA_{i,t-1} + \beta_7 \Delta lnTA_{i,t-1} +$$

$$\beta_8 \Delta RWA\_TA_{i,t-1} + YEAR\_FE + \Delta \varepsilon_{i,t} \qquad (1)$$

where the Δ is the first difference operator. The dependent variable takes two different values: i) the flows of new UTP over gross loans, i.e. the portion of performing loans that increases the amount of UTP during the year compared to gross loans (from PL to UTP); ii) the flows of new bad loans over gross loans, i.e. the portion of performing loans that become bad loans during the year compared to gross loan (from PL to bad loans). In this way, we specifically analyse the deterioration of performing loans which downgrade to UTP and to bad loans. Compared to the level of NPL at the end of the year or to the changes in stocks over time, the use of new flows of impaired loans as alternative proxy of credit portfolio quality give a more precise view on the deterioration of exposures in the typical first stage of loan decay. As noted above, there are a few studies in literature that investigate the determinants of the new flows of impaired loans. But they investigate only new flows of bad loans, without considering the other classes of NPL, and they do not analyze out-flows from specific categories of impaired loans to other NPL or to performing loans (Bofondi and Gobbi, 2004; Quagliariello, 2008; Marcucci and Quagliariello, 2009; Bofondi and Ropele, 2011).

We also add the year fixed effect as an alternative for the macroeconomic variables, which are the same for all banks in the sample, in order to capture the differences in the time that are not captured by other variables.

Among bank specific variables, in line with the literature (Radlet and Sachs, 1998; Keeton, 1999; Rajan and Dhal, 2003; Podpiera and Weill, 2008; Foos et al., 2010 ; Louzis et al., 2012; Klein, 2013; Chaibi, 2016 ; Cucinelli et al., 2018), we consider factors which explain lending activity, measured by the growth of gross loans year on year (GRGL); the level of capitalization, measured by Tier 1 ratio (Tier1); profitability, proxied by the return on equity (ROAE); and cost efficiency, proxied by the cost to income ratio (COST_INCOME), which measures the ratio between operating costs

(administrative and fixed costs, such as salaries and property expenses) and operating income. We add also some control variables: the bank business model, proxied by the gross loans over total assets (GL_TA); risk appetite, proxied by the risk weighted assets density (RWA_TA); and bank size, proxied by the natural logarithm of total assets (Ln_TA) (Shrieves and Dahl, 1992, Aggarwal and Jacques, 2001 and Rime, 2001). Consistently with the credit risk determinants literature (Bofondi and Ropele, 2011; Cucinelli et al., 2018), we include variables with a one-year lag.

In the second part of our analysis, in order to detect the determinants of the decrease of UTP, we run another regression, using a two-step system GMM model with robust standard errors. In this case, we base our analysis on a subsample of banks for which data of the flows are available. The subsample is made up of 56 banks, which represent 70.82% of the total assets of the Italian banking system at the end of 2016 and 98.62% of the total assets of our sample in 2016.

$$\Delta Out\_flow_{i,t} = \beta_1 \Delta Out\_flow_{i,t-1} + \beta_2 \Delta MANAGE_{i,t-1} + \beta_3 \Delta PROVISIONS_{i,t-1} + \beta_4 \Delta TIER1_{i,t-1} + \beta_5 \Delta ROAE_{i,t-1} + \beta_6 \Delta COST\_INCOME_{i,t-1} + \beta_7 \Delta GRGL_{i,t-2} + \beta_8 \Delta GL\_TA_{i,t-1} + \beta_9 \Delta lnTA_{i,t-1} + \beta_{10} \Delta RWA\_TA_{i,t-1} + YEAR\ FE + \Delta \varepsilon_{i,t} \quad (2)$$

The dependent variables of (2) are: i) the out-flows of UTP to performing loans over the stock of UTP (flow to PL); and ii) the out-flows of UTP to other categories of NPL (bad loans in particular) over the stock of UTP (flow to NPL). The first variable thus reflects an improvement in customer creditworthiness, and the second a worsening in credit quality. As instrumental variables we include the first difference of dependent variables at time t-1 ($\Delta Out\_flow_{i,t-1}$).

As a bank specific variable which may impact on UTP out-flows, we consider the presence of a specialized structure dedicated to the management of NPL, proxied by a category variable equal to 1 if the bank states in the balance-sheet report that impaired loans are managed by the legal office or by another office not specialized in managing NPL; equal to 2 if a specific office that aims to recover

non-performing loans exists or if the bank uses an external office with the same purpose (as do cooperative banks); equal to 3 if the bank has a specific non-core unit to manage NPL; and equal to 0 if the bank does not explain in the balance-sheet how it manages NPL (MANAGE). We include the MANAGE variable only in the second analysis, because the unit/office aims to manage NPL rather than performing loans. We believe it can directly affect the amount of NPL, but is probably not able to prevent the deterioration of performing loans.

We also insert the loan loss provisions for UTP over the stock of UTP ratio (PROVISIONS), which indicates the coverage rate of UTP. We include this variable only in the second analysis because it does not refer to performing loans. On the other hand, it may be an important determinant of the out-flows from UTP, both to performing exposures and bad loans.

We also use the same set of variables as in the previous analysis: bank profitability and bank efficiency, proxied respectively by the ROAE and the cost to income ratio (COST_INCOME); bank business model, proxied by the gross loans over total assets (GL_TA); the growth of gross loans (GRGL); risk appetite, proxied by the risk weighted assets over total assets (RWA_TA); bank size, proxied by the natural logarithm of total assets (ln_TA), and capitalization, measured by Tier 1 capital ratio (TIER 1) (Jimenez and Saurina, 2006, Foos et al., 2010). In this regression model too, all independent and control variables are included with one lag (t-1). We also insert the same year fixed effect vector to control for the time period observed.

To test the absence of correlation between the instruments and error term, we carry out the Sargan test. In addition, we test the presence of first- and second-order autocorrelations in the first differenced residuals (AR-1 and AR-2).

Table 1 reports the description of the variables used in the GMM models.

Table 1 approximately here

The descriptive statistics and the correlation matrix are reported in Tables 2 and 3. Our results show no high Pearson correlation between independent variables, and the most of coefficients are statistically significant. Looking at the descriptive statistics, we observe that the average value of flows from performing loans to UTP is higher than that of flows from performing loans to bad loans. This suggests that loans *in bonis* usually move into the intermediate class of NPL (i.e. the UTP) before becoming bad loans. With regard to the out-flows from UTP to performing loans and other NPL, the average value shows that the amount of loans which worsen and become bad loans is much higher than the amount of exposures which improve and go back to being performing loans, showing the difficulties in the management and recovery of UTP (Table 2). Regarding bank structure, the descriptive statistics show a good capitalization of banks, with an average Tier 1 ratio equal to 11.78%, and a low but positive profitability, with an average ROAE of 0.8%. In terms of business model, as a result of the sample definition criteria, banks show a high ratio of gross loans over total assets, ranging from 41% to 96%, with an average value of 68%. This confirms that lending activity is the core business for banks in our sample for the whole analyzed period. Lastly, with regard to the level of coverage ratio of UTP, the average value is equal to 20%, showing the need for banks to improve provisions for UTP in the near future, in line with regulations on capital requirements and the supervisory expectations for prudential provisioning (Table 2).

Table 2 approximately here

Table 3 approximately here

5. Results

5.1 Determinants of new flows of UTP and bad loans

The first results show the determinants of the flow of new UTP and new bad loans from performing loans, reported in Table 4.

Table 4 approximately here

The first hypothesis, regarding lending activity and the quality of portfolio, is confirmed in the case of both UTP and bad loans. The results show a positive relationship between the growth of gross loans and the dependent variable, confirming findings of previous literature about NPL in general (Berger and Udell, 2004; Dell'Arriccia and Marquez, 2006; Vithessonthi, 2015). In particular, an increase of 1% in the growth of gross loans at time t-1 leads to an increase of 3.5% in the UTP ratio and 6.19% in the bad loans ratio, as shown in Table 4. The adoption of an expansive lending policy leads to a fast deterioration in credit portfolio quality. The growth of gross loans may imply that banks also tend to lend to more risky customers, and this may be due to the change in the bank standards, from tightness to laxity (Asea and Blomberg, 1998; Lown and Morgan, 2006).

In terms of capitalization, our findings suggest that banks with higher regulatory capital – proxied by the Tier1 ratio – show higher flows of both new UTP and new bad loans. We thus confirm for each class of NPL the findings of Barth et al. (2004), Macit (2012), Ghosh (2015) and Cucinelli (2018), who verified a positive relationship between the banks' capitalization and their NPL. Specifically, an increase of 1% in Tier 1 ratio leads on average to a rise in the UTP ratio of 18.8% and in the bad loans ratio of 14.7%. The analysis of new flows of UTP and bad loans confirms the effect of prudential regulation which aims to curb moral hazard incentives by imposing risk-sensitive capital requirements.

The procyclical credit policy hypothesis is borne out by the deterioration of performing loans into both UTP and bad loans. This is in line with Poghosyan and Cihak (2011) who show how European banks with good earnings profiles are more likely to experience distress in the upcoming year. Similarly, Louzis et al. (2012) provide empirical evidence that performance may serve as a leading indicator for future problem loans. In this case too, the positive relationship is confirmed for both classes of NPLs which show average increases of 5.9% for UTP ratio and 2.7% for bad loans ratio when the ROAE rises of 1%. This suggests that banks oriented to high performance may accept higher risk in their lending activity. Banks achieve higher profits, but they also see an increase in impaired loans and a deterioration of their portfolio quality as a consequence.

Looking at the cost income ratio, we observe a positive relationship between this measure and the new flows of performing loans to UTP. There is an average increase of 3% in UTP ratio when the cost income ratio rises by 1%. However, the relationship is not significant when we consider the flow from performing loans to bad loans. Looking at new flows of UTP, banks with a higher cost efficiency show a better credit portfolio quality, in line with Louzis et al. (2012) and Cucinelli et al. (2018). Good managers are able to contain operating costs, yielding a low cost to income ratio, and, at the same time, they keep credit portfolio quality high. On the other hand, bank managers with poor skills in credit scoring and monitoring increase costs and make poor quality loans.

We also find evidence that banks with higher RWA density are more subject to loan portfolio deterioration: an increase in RWA density of 1% leads to an increase in UTP ratio of 12.6% and in bad loans ratio of 17.6%. Our results confirm that banks which define a riskier policy are also willing to accept a higher level of non-performing loans in their credit portfolio.

With regard to the lending activity – proxied by the ratio of gross loans over total assets – it seems that banks more oriented to lending are more exposed to higher performing loans that become UTP than to bad loans.

In term of magnitude of coefficients, although several variables show statistical significances, our findings suggest that bank capitalization and risk appetite, together with the level of NPL in the previous year, have a greater impact on dependent variables when the regressors rise by 1%.

The Hansen test shows that the instruments used are not correlated with the residuals. With regard to the Arellano-Bond (AR) tests, looking at the flows, the hypothesis that errors are not auto correlated can be rejected in the first order (AR(1)), but not in the second order (AR(2)). For the UTP and bad loans ratio, the tests make it possible to reject the hypothesis that autocorrelation is absent among errors at both first and second order (AR(1) and AR(2)).

5.2 Determinants of UTP out-flows

Table 5 reports results of the second part of our research, the analysis of the out-flows from UTP to both performing and other NPL, testing Hypothesis 4.

Table 5 approximately here

Concerning impaired loans that return *in bonis*, a positive statistically significant relationship between the MANAGE variable and the dependent variable is observed, in line with our expectations. This result suggests that the presence of a specific non-core unit/office totally dedicated to the credit risk management leads to an improvement in credit portfolio quality. The findings underline that with regard to the flows from UTP to performing loans, proactive management plays a more important role than for out-flows to other NPL. In fact, in this second case, no significant relationship is observed.

Our findings emphasize that banks more oriented to lending activity – i.e. with a higher gross loans over total assets ratio – are more successful in managing the credit portfolio. In fact, our results reveal a negative and significant relationship between the gross loans over total assets ratio and the flow from UTP to NPL.

Concerning efficiency, the bad management hypothesis is confirmed for the progressive deterioration of credit quality: when cost income ratio increases, banks show a growth in new flows of UTP, as well as a higher transition from UTP to bad loans. On the other hand, cost income ratio is not a significant variable in determining the return *in bonis* of impaired loans. In this case, the presence of an organizational structure dedicated to NPL management is one of the most relevant factors impacting on the out-flows from UTP to performing loans. Although investment in a dedicated structure may increase operating costs without producing income directly, it is essential for reducing impaired positions.

Results related to determinants of out-flows from UTP confirm the risk sensitivity of regulatory capital: Tier 1 ratio is negatively correlated to out-flows towards performing loans, and positively correlated to out-flows towards other NPL.

Results of the GMM models show no significant evidence of serial correlation in the first order-differenced errors at Order 2 (AR2). The Hansen-test shows that the instruments used are not correlated with the residuals.

6. Robustness test and additional analysis

6.1 Robustness test: Alternative bank-specific and macroeconomic variables

To check the robustness of our results we run further regressions to measure bank specific characteristics in our main models. First, in addition to ROAE, we use the ROAA, the net interest margin and the net income over gross revenues, to focus solely on bank core activity. The results show similar significance and magnitude to the main findings.

In further analysis, instead of the year fixed effect vector, we insert macroeconomic variables, such as the inflation and the unemployment rates, GDP and house price index, at time t-1 (Ghosh, 2015). Because the analysis is a case study on a single country, these macroeconomic variables do not show differences between banks, but they capture the trend of the economic cycle during the period under investigation. We thus believe that the year fixed effect vector is more able to capture the differences in the time that are not captured by other variables.

6.2 Additional analysis: Alternative model specification

Two-step system GMM estimation is the best method in the case of a dynamic panel and for the analysis of the determinants of impaired loans, as noted in previous literature (Arellano and Bover, 1995; Blundell and Bond, 1998). However, in this section we check the coefficients obtained from alternative model specifications. We test different hypotheses on individual effects, and we hypothize that the feedback effect does not exist in our analysis (we run static economic models without the

lagged dependent variable as instrumental variable). Therefore, we run both random effect and fixed effect estimation methods, following previous literature (Klein, 2013; Ghosh, 2015; Beck et al., 2015).

In estimating random effects, we can solve the problem implied in the OLS regression by implementing an individual specific intercept in our model, which is assumed to be random. However, in estimating random effects full exogeneity of our model is implied. Given that there is some endogeneity in this analysis, results obtained from this model are thus not consistent.

We also estimate fixed effects. But neither in this case are results directly comparable with system GMM findings of our main analysis, because GMM estimates are for a dynamic panel model while fixed-effect estimates are for static models. The fixed-effect estimator makes it possible to control for unobserved heterogeneity across banks. This approach is intuitive and somewhat simple, and may give rise to "dynamic panel bias", which results from the possible endogeneity of the lagged variable and the fixed effects in the error term, $u_{i,t}$ (Klein, 2013).

For the fixed effect and random effect estimations, we run the Hausman test to detect which of the two estimators is better. The test shows a large and significant Hausman statistic, implying a large and significant difference. The null hypothesis that the two methods work correctly is thus rejected, in favour of the alternative hypothesis that one (fixed effects) is better than the other (random effects).

We also run a pooled Ordinary Least Squares (OLS) regression (Williams, 2004). However, OLS is more appropriate for cross-sections or time series data than for panel data, and the results are not robust. The pooled OLS estimation is simply an OLS technique run on panal data, so individually specific effects are completely ignored. Many basic assumptions, such as orthogonality of the error terms, are thus violated. However, in order not to consider the observations as independent, in our model we cluster standard errors at bank level. To test the difference between the random fixed effects and pooled OLS methods, we run the Breusch and Pagan Lagrangian multiplier test. The results do not lead us to reject the null hypothesis, which means the pooled OLS estimator is preferable.

Finally, as the last additional analysis, we run the Generalized Least Square (GLS) regression. This however is more appropriate where panel data is structured with many T and few N, whereas our panel data has more banks than years observed. Autocorrelation thus requires attention, so we specify that, within each panel, there is AR(1) autocorrelation and that the coefficient of the AR(1) process is specific to each panel. In fact, if the autocorrelation within panels does not exist, the GLS has the same structure as OLS and results are the same.

In all these models, to obtain consistent and not biases coefficients, we do not include the lagged dependent variable. This is coherent with the basics of static economic models, compared to dynamic models such as GMM.

Table 6 approximately here

Table 6 reports results of the additional analyses, which in very few cases show similar results to our main analysis, such as in the case of size and growth of gross loans (with regard to the flow from PL to bad loans). The other variables do not show any statistically significant relationship with the dependent variables or, in few cases, the sign of the relationship is different from that obtained in the main analysis, as in the case of RWA density and cost to income ratio, which show a negative relationship with the dependent variable. We obtain different results from our main analysis because the assumptions under these static models differ from those of the dynamic two-step system GMM model. We believe that the two-step system GMM model is preferable because it reduces finite sample bias and any other imprecision by regressing the changes in deteriorated loans, using its lagged variable as an instrument.

We also run the same estimator methods for the second step of our analysis: the out-flow from UTP both to performing loans and other NPL classes. Findings are reported in Table 7.

Table 7 approximately here

Results are similar to those of the main analysis. In particular, the specific unit/office to manage NPL improves flows from UTP to performing loans, increasing credit portfolio quality, although the coefficients are really small.

However, the observations made above are also valid here. Our data-set is a dynamic panel, which leads us to believe that the two-step system GMM method is the best econometric estimator. The additional analyses identify biases and do not yield consistent results.

7. Conclusions and policy implications

NPL remains one of the main threats to the stability of the European financial system. Partly because of the new supervisory expectations for prudential provisioning and the introduction of new accounting standards, analysts expect that UTP exposures and the UTP coverage rate will increase in the near future, strongly affecting bank economic results (PWC, 2018). UTP account for a high portion of NPL and, because of their current lower coverage, they present a relatively high net value compared to other classes. Moreover, UTP are particularly complex to manage: they require the bank to carry out ongoing due diligence on each borrower in order to select the right strategic option. When the strategy for managing these exposures is a restructuring process rather than liquidation of underlying assets, the operation is particularly complex and expensive for banks. UTP in fact retain a "living" counterpart which often requires operational and financial support to be restructured. It is important to evaluate the benefits of this process in comparison with other managerial strategies, such as single- name and portfolio transactions, as well as securitization operations. For banks, close knowledge of the determinants of these exposures and their potential flows towards other NPL or performing loans is extremely important (Temesvary and Banai, 2017).

In order to deepen the analysis on this specific category of NPL, the study investigates the determinants of the annual new flows of UTP at bank level, as well as the determinants of the flow of UTP which return *in bonis* or which move to bad loans.

First, studying the impaired exposures of the Italian banking system during the period 2010-2016, the analysis tests whether the determinants of NPL at bank level identified by the literature are confirmed for the different classes of deteriorated loans. In particular, we test hypotheses on lending policy, bank capital, bad management, and procyclical credit policy.

As in traditional literature about NPL, lending policy and procyclical credit policy hypotheses are also accepted separately for the different categories of impaired exposures, both UTP and bad loans. In fact, we found a positive relationship between the growth of gross loans and new flows from performing to deteriorated loans. Besides, banks with a good economic performance are more likely to experience a high level of UTP and bad loans in the following year: managers oriented to obtain high returns in the short term can operate at the expense of credit quality.

On the other hand, results about the actual relationships between capitalization and credit portfolio quality, as well as between operating costs faced by banks and impaired loans are more ambiguous in the literature on NPL. It is thus particularly important to test these hypotheses on the different classes of impaired loans separately.

Concerning the level of capitalization, our results show a positive relationship between the capital ratio and new flows of both UTP and bad loans. Moreover, Tier 1 ratio is negatively correlated to out-flows towards performing loans, but positively correlated to out-flows towards other NPL.

The literature shows that there is no clear consensus on the relationship between the level of capitalization and the NPL ratio. Alongside studies that reveal a positive relation (Barth et al., 2004; Godlewski, 2005; Boudriga et al., 2009; Macit, 2012; Ghosh, 2015; Cucinelli, 2018), other authors find an opposite association between the two variables (Keeton and Morris, 1987; Berger and DeYoung, 1997; Jimenez and Saurina, 2006; Podpiera and Weill, 2008; Louzis et al., 2012; Klein, 2013; Makri et al., 2014; Chaibi, 2016). These discordant results are probably due to the nature of NPL ratio, that represents an ex post measure of risk-taking, as well as to the role of regulatory capital. A higher level of capital might serve as a tool to prevent banks from being insolvent. In fact, it allows banks to absorb shocks on the credit market. On the other hand, higher capital may also stimulate

banks to take more risk in supplying credit. The regulations on capital adequacy in fact mean that only banks with a high level of capital can (consciously) accept high credit risks. According to our results, banks with higher level of capitalization experience a higher level of non-performing loans, probably due to the previous engagement in more risky activities. Without postulating the precence of a casuality between bank capital requirement and NPL, our results can only underline a negative relathionship between the two variables, suggesting that banks with higher capital requirement are more willing to disburse risker loans that can become UTP in the subsequent years.

Concerning operating costs, the bad management hypothesis is confirmed for UTP, whereas the relationship between cost efficiency and new flows of deteriorated exposures is not significant for bad loans. Our results show that poor management, proxied by the decrease in efficiency, implies lower credit quality: an increase in cost-income ratio is correlated with both a growth of performing loans that become UTP, and a growth of UTP which deteriorate into bad loans. On the other hand, cost income ratio does not affect the flows of UTP that return *in bonis*. Efficient cost management is a prerequisite to reduce the progressive deterioration of credit quality, but it is not useful in encouraging the transition to performing portfolio of loans able to return *in bonis*. The investigation on the different categories of NPL confirms that interpretation of the variables related to the management of credit risk requires more in-depth analysis. Our study tests the impact of investments in organizational structures for the management of impaired loans, examining separately out-flows from UTP to performing loans compared to out-flows from UTP to bad loans. This analysis makes it possible to distinguish the reduction in the level of UTP that occurs when the credit merit of loans either improves or worsens. Our findings confirm that banks with a proactive organization dedicated to NPL management show a higher flow from UTP to performing loans, suggesting that these banks are able to improve the quality of their credit portfolio. A non-significant relationship was however observed between the proactive and dedicated management of NPL and the flows between UTP and other categories of deteriorated loans.

The existence of a specific business unit specialized in the management of NPL allows banks to improve the proactive recovery and management of impaired loans, encouraging the transition to a performing portfolio, and to focus the rest of the bank on the core activity. On the other hand, these organizational structures appear unable to limit the degree of deterioration in impaired positions.

In general, the findings reveal the importance of sound and dedicated UTP management. This is particularly important today, since the current coverage ratio for UTP makes the sale of these loans more difficult and expensive compared to bad loans.

The research has two main limitations. The first is the small size of the sample of banks, and the second is that the case study is limited to a single country. Both limitations reflect the difficulty of collecting data on UTP. In fact, to the best of our knowledge, at the time of writing, information on annual increases and decreases of UTP, and their causes, is not shown in annual reports of banks except for those of the main Italian banks. This makes it impossible to build an international sample. However, Italy is clearly a significant case study given that one third of the European NPL, and consequently UTP, are held in the Italian banking system. Since a high proportion of European NPL are Italian exposures, our findings are relevant for the overall problem of NPL in Europe. We are thus confident that our research can serve as a foundation for future studies on UTP determinants, facilitated by the harmonization of NPL definitions, as well as accountability standards across Europe.

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List of Tables

Table 1. Variables description

Variable	Description	Source	Sign expected
Dependent variables			
from PL to Bad Loans	Flow of new Bad Loans from Performing loans over the stock of gross loans at the end of the previous year (t-1)	Table A.1.7 in the Additional information of balance sheet (data hand collected) The flow is available in the bank's balance-sheet.	/
from PL to UTP	Flow of new UTP from Performing loans over the stock of gross loans at the end of the previous year (t-1)	Table A.1.7 in the Additional information of balance sheet (data hand collected)	/
Flow to PL	The out-flow from UTP to performing loans over the stock of unlikely-to-pay loans	Table A.1.8 in the Additional information of balance sheet (data hand collected) The flow is available in the bank's balance-sheet.	/
Flow to NPL	The out-flows from UTP to other categories of NPL over the stock of unlikely-to-pay loans	Table A.1.8 in the Additional information of balance sheet (data hand collected) The flow is available in the bank's balance-sheet.	/
Independet variables			
Tier 1	Tier 1 over risk weighted assets as measure of bank capitalization	SNL Unlimited	+
ROAE	Return on average equity as measure of profitability	SNL Unlimited	+/-
COST_INCOME	Cost to income ratio as measure of bank efficiency	SNL Unlimited	+/-
GRGL	Growth of gross loans as measure of lending activity	SNL Unlimited	+
MANAGE	Category variable equal to 1 if bank states in the balance-sheet report that the problem loans are managed by the legal office or by another office not specific in managing NPL; 2 for a specific office that aims to recover non performing loans and if bank adopts an external office (i.e. cooperative banks); 3 if bank has a specific non core unit to manage NPL; 0 if bank does not explain in the balance-sheet how NPL are managed	Balance sheet	+ (with out-flow to PL) - (with out-flow to NPL)
Control variables			
GL_TA	Gross loans over total assets as proxy of bank business model	SNL Unlimited	+
RWA_TA	Risk weighted assets over total assets as proxy of bank risk appetite	SNL Unlimited	+
Ln_TA	The natural logarithm of total assets as measure of bank size	SNL Unlimited	-
PROVISIONS	Loan loss provisions specific for UTP over total UTP	Balance sheet	No relationship (with out-flow to PL) + (with out-flow to NPL)

Note: Table 1 reports all the variables adopted in the econometric model, with the definitions, the sources and the expected signs

Table 2. Descriptive statistics

	N	Mean	p50	min	max	sd
flow_from_PL_to_Bad Loans	557	.051	.032	0	.391	.083
from PL_to_UTP	385	.138	.057	0	1.055	.148
flow_to_PL	418	.243	.203	0	1.536	.207
flow_to_NPL	418	.353	.321	0	1.677	2.098
Tier1	559	.117	.111	.016	.484	.047
ROAE	520	.008	.028	-1.07	1.060	.144
GRGL	510	.051	.012	-.743	2.35	.184
COST_INCOME	557	.657	.656	.204	2.308	.142
GL_TA	561	.680	.699	.411	.960	.146
RWA_TA	559	.614	.632	.057	.952	.145
ln_TA	563	1.59	1.54	1.31	2.076	1.730
MANAGE	594	.474	0	0	3.00	1.009
PROVISIONS	246	.207	.198	.007	.442	.077

Note: Table 2 shows the descriptive statistics (number of observations, mean, median, minimum, maximum and standard deviation) of: the flows from performing to bad loans (flow_from_PL_to_Bad loans); the flows from performing to UTP (from PL_to_UTP); the flows from UTP to performing loans (flow_to_PL); the flows from UTP to other categories of NPL (flow_to_NPL); the capitalization measure (Tier1 ratio); the profitability ratio measured by the return on average equity (ROAE); the growth of gross loans (GRGL); the cost to income ratio (COST_INCOME); the proxy of business model measured by gross loans over total assets (GL_TA); the risk weight assets density (RWA_TA); size measured by the natural logarithm of total assets (ln_TA); the category variable equal to 1 if bank states in the balance-sheet report that problem loans are managed by the legal office or by another office not specific in managing NPL; 2 if there is a specific office that aims to recover non performing loans or if the bank adopts an external office (e.g. cooperative banks); 3 if bank has a specific non core unit to manage NPL; 0 if bank does not explain in the balance-sheet how NPL are managed (MANAGE); and finally the loan loss provisions for UTP over gross loans (PROVISIONS).

Table 3. Correlation matrix

		Tier1	ROAE	GRGL	COST_INCOME	GL_TA	RWA	ln_TA	PROVISIONS	MANAGE
TIER1	Pearson Correlation	1.000								
	Sig. (2-tailed)									
	N	502								
ROAE	Pearson Correlation	0.217**	1.000							
	Sig. (2-tailed)	.000								
	N	467	469							
GRGL	Pearson Correlation	0.125**	0.295**	1.000						
	Sig. (2-tailed)	.007	0.000							
	N	468	466	470						
COST_INCOME	Pearson Correlation	-0.122**	-0.546**	-0.144**	1.000					
	Sig. (2-tailed)	0.007	0.000	0.002						
	N	496	466	465	499					
GL_TA	Pearson Correlation	-0.376**	-0.308**	-0.176**	0.192**	1.000				
	Sig. (2-tailed)	0.000	0.000	0.000	0.000					
	N	500	469	470	497	503				
RWA	Pearson Correlation	-0.355**	-0.145**	-0.142**	0.046	0.777**	1.000			
	Sig. (2-tailed)	0.000	0.002	0.002	0.309	0.000				
	N	502	467	468	496	500	502			
ln_TA	Pearson Correlation	-0.323**	-0.076	-0.037	0.055	0.021	-0.174**	1.000		
	Sig. (2-tailed)	0.000	0.098	0.424	0.223	0.631	.000			
	N	502	469	470	499	503	502	505		
PROVISIONS	Pearson Correlation	0.022	-0.264**	-0.217**	0.090	-0.085	-0.295**	0.249**	1.000	
	Sig. (2-tailed)	0.731	0.000	0.001	0.163	0.182	0.000	0.000		
	N	246	246	244	244	246	246	246	246	
MANAGE	Pearson Correlation	0.091*	-0.003	0.015	-0.040	-0.182**	-0.305**	0.105*	0.328**	1.000
	Sig. (2-tailed)	0.041	0.955	0.739	0.367	0.000	0.000	0.018	0.000	
	N	502	469	470	499	503	502	505	246	514

Note: Table 3 shows the Pearson correlation matrix of: the capitalization measures (Tier1 ratio); the profitability ratio measured by the return on average equity (ROAE); the growth of gross loans (GRGL); the cost to income ratio (COST_INCOME); the proxy of business model measured by gross loans over total assets (GL_TA); the risk weight assets density (RWA_TA); the size measured by the natural logarithm of total assets (ln_TA); the category variable equal to 1 if bank states in the balance-sheet report that problem loans are managed by the legal office or by another office not specific in managing NPL; 2 if there is a specific office that aims to recover non-performing loans and if bank adopts an external office (e.g. cooperative banks); 3 if bank has defined a specific non-core unit to manage NPL; 0 if bank does not explain in the balance-sheet how NPL are managed (MANAGE); and finally the loan loss provisions for UTP over gross loans (PROVISIONS).
**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 4. Results of determinants of flow from performing loans to UTP and flow from performing loans to Bad Loans

VARIABLES	**From PL to UTP**	**From PL to Bad Loans**
Constant	0.825***	-0.985***
	(0.19)	(0.18)
Dependent variable (t-1)	0.387***	0.278***
	(0.02)	(0.01)
GRGL(t-1)	0.0353***	0.061***
	(0.00)	(0.00)
Tier1(t-1)	0.188*	0.147***
	(0.10)	(0.04)
ROAE(t-1)	0.059***	0.027***
	(0.01)	(0.00)
COST_INCOME(t-1)	0.030***	-0.002
	(0.03)	(0.01)
RWA_TA(t-1)	0.126***	0.176***
	(0.04)	(0.02)
Ln_TA(t-1)	-0.068***	0.055***
	(0.01)	(0.01)
GL_TA(t-1)	0.063*	-0.024
	(0.03)	(0.02)
YEAR FE	YES	YES
Observations	**372**	**426**
Number of banks	**62**	**71**
AR1	0.0024	0.0011
AR2	0.1694	0.207
Hansen test (prob chi2)	0.8719	0.6987
Sargan (prob chi2)	0.000	0.028

Note: The regression run is a system GMM two step regression and the robust standard errors are reported in brackets. The table reports results referring to the determinants of the UTP both in term of ratio and in term of flows from performing loans to UTP. The dependent variables are: the flows from performing loans to Bad Loans (from PL to ban loans); the flows from performing loans to UTP (from PL to UTP). The explanation variables are: the capitalization measure (Tier1 ratio); the profitability ratio measured by the return on average equity (ROAE); the growth of gross loans (GRGL); the cost to income ratio (COST_INCOME). We insert the following into the bank specific controls: the proxy of business model measured by gross loans over total assets (GL_TA); the risk weight assets density (RWA_TA); the size measured by the natural logarithm of total assets (ln_TA). Asterisks denote significance at: *** p<0.01, ** p<0.05, * p<0.1

Table 5. Results of determinants of out-flows from UTP

VARIABLES	OUT-FLOW TO PL	OUT-FLOW TO NPL
Constant	1.721**	1.509
	(0.75)	(1.25)
DEPENDENT (t-1)	0.401***	0.181***
	(0.02)	(0.04)
MANAGE	0.017***	-0.006
	(0.00)	(0.00)
PROVISIONS(t-1)	-0.059	0.928***
	(0.05)	(0.15)
Tier1(t-1)	-1.057***	1.170*
	(0.25)	(0.66)
ROAE(t-1)	0.051**	0.365***
	(0.02)	(0.06)
COST_INCOME(t-1)	0.135	0.356***
	(0.03)	(0.09)
GRGL(t-1)	-0.061	0.091
	(0.04)	(0.06)
RWA_TA(t-1)	0.070	0.339*
	(0.03)	(0.24)
Ln_TA(t-1)	-0.098**	-0.097
	(0.04)	(0.06)
GL_TA(t-1)	0.013	-0.750***
	(0.09)	(0.26)
YEAR FE	YES	YES
Observations	157	157
Banks	41	41
AR1	0.0033	0.0002
AR2	0.5858	0.8782
Hansen test (prob chi2)	0.1343	0.3615
Sargan test (prob chi2)	0.0012	0.0002

Note: The regression run is a GMM two step regression and the robust standard errors are reported in brackets. The table reports the results referring to the decrease of UTP, both in positive and negative terms. The dependent variables are the flows from UTP to performing loans (PL) and the flows from UTP to other non performing loans (NPL). The explanatory variables are: the flows from UTP to performing loans (flow_to_PL); the flows from UTP to other categories of NPL (flow_to_NPL); the category variable is equal to 1 if bank states in the balance-sheet report that the problem loans are managed by the legal office or by another office not specific in managing NPL; 2 if there is a specific office that aims to recover non performing loans and if bank adopts an external office (e.g. cooperative banks); 3 if bank has a specific non core unit to manage NPL; 0 if bank does not explain in the balance-sheet how NPL are managed (MANAGE); and finally the loan loss provisions for UTP over gross loans (PROVISIONS). The capitalization measures are as follows: (Tier1 ratio); the profitability ratios, respectively the return on average equity (ROAE); the growth of gross loans (GRGL); the cost to income ratio (COST_INCOME); the proxy of business model measured by gross loans over total assets (GL_TA); the risk weight assets density (RWA_TA); the size measured by the natural logarithm of total assets (ln_TA) . All variables are at time t-1. The asterisks denote respectively significance at: *** p<0.01, ** p<0.05, * p<0.1

Table 6 Robustness checks using different estimator methods: determinants of new flows from PL to both UTP and Bad Loans

	Fixed effects		Random effects		OLS Pooled		GLS	
VARIABLES	**From PL to UTP**	**From PL to Bad Loans**	**From PL to UTP**	**From PL to Bad Loans**	**From PL to UTP**	**From PL to Bad Loans**	**From PL to UTP**	**From PL to Bad Loans**
Constant	1.741**	-0.772**	1.025***	0.033	1.305***	0.068	1.046***	0.026
	(0.72)	(0.30)	(0.17)	(0.05)	(0.21)	(0.06)	(0.14)	(0.05)
GRGL(t-1)	-0.039	0.013	-0.028	0.039***	-0.071***	0.050***	-0.026	0.034**
	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Tier1(t-1)	-0.004	0.000	0.000	0.000	0.002	0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ROAE(t-1)	0.018	-0.005	-0.043	-0.005	-0.107	-0.018	-0.028	-0.001
	(0.06)	(0.02)	(0.06)	(0.02)	(0.08)	(0.01)	(0.05)	(0.02)
COST_INCOME (t-1)	0.137	-0.078**	-0.000	-0.069**	-0.210	-0.041	-0.030	-0.037
	(0.09)	(0.03)	(0.08)	(0.03)	(0.13)	(0.03)	(0.07)	(0.02)
RWA_TA(t-1)	0.053	0.049	-0.028	0.042	-0.172*	0.053	-0.053	0.046
	(0.15)	(0.06)	(0.11)	(0.04)	(0.10)	(0.05)	(0.11)	(0.04)
Ln_TA(t-1)	-0.109***	0.044***	-0.056***	-0.001	-0.052***	-0.001	-0.052***	-0.001
	(0.04)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GL_TA(t-1)	0.106	0.160***	-0.006	0.034	-0.050	0.005	-0.104	0.010
	(0.14)	(0.05)	(0.10)	(0.03)	(0.12)	(0.04)	(0.09)	(0.03)
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	286	363	286	363	286	363	285	362
R-square between	0.2226	0.248	0.1736	0.056	-	-	-	-
R-square within	0.3233	0.0005	0.4361	0.241	0.412	0.169	-	-
R-squared overall	0.2720	0.0067	0.3614	0.1611	-	-	-	-
Number of SNLkey	57	72	57	72	-	-	57	72
AR(1)	-	-	-	-	-	-	0.4171	0.3736

Note: Table reports results of Fixed effects, Random effects, Pooled OLS (with clustered standard errors) and GLS estimator methods as robustness checks. The robust standard errors are reported in brackets. The table reports results referring to the determinants of the UTP both in term of ratio and in term of flows from performing loans to UTP. The dependent variables are: the flows from performing loans to Bad Loans (from PL to ban loans); the flows from performing loans to UTP (from PL to UTP). The explanation variables are: the capitalization measure (Tier1 ratio); the profitability ratio measured by the return on average equity (ROAE); the growth of gross loans (GRGL); the cost to income ratio (COST_INCOME). We insert the following into the bank specific controls: the proxy of business model measured by gross loans over total assets (GL_TA); the risk weight assets density (RWA_TA); the size measured by the natural logarithm of total assets (ln_TA). Asterisks denote significance at: *** p<0.01, ** p<0.05, * p<0.1

Table 7 Robustness checks using different estimator methods: Determinants of Out-flows to both PL and other NPL classes

	Fixed effects		Random effects		OLS Pooled		GLS	
VARIABLES	OUT-FLOW TO PL	OUT-FLOW TO NPL	OUT-FLOW TO PL	OUT-FLOW TO NPL	OUT-FLOW TO PL	OUT-FLOW TO NPL	OUT-FLOW TO PL	OUT-FLOW TO NPL
Constant	2.684*	1.055	0.066	0.317	0.095	0.570***	-0.000	0.293
	(1.47)	(2.17)	(0.19)	(0.26)	(0.16)	(0.20)	(0.14)	(0.19)
MANAGE	0.002*	-0.003	0.003	-0.009	0.002**	-0.017	0.006*	-0.014
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
PROVISIONS (t-1)	-0.050	0.854***	-0.022	0.758***	0.000	0.620***	0.007	0.680***
	(0.14)	(0.21)	(0.12)	(0.17)	(0.15)	(0.22)	(0.11)	(0.16)
Tier1(t-1)	-0.009	0.001	0.001	-0.003	0.003	-0.004	0.003	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ROAE(t-1)	0.135**	0.235**	0.092	0.257***	0.106	0.248***	0.065	0.292***
	(0.06)	(0.09)	(0.05)	(0.08)	(0.07)	(0.07)	(0.05)	(0.08)
COST_INCOME (t-1)	0.205**	0.140	0.183**	0.176	0.151	0.192	0.165**	0.225*
	(0.09)	(0.14)	(0.08)	(0.12)	(0.16)	(0.14)	(0.07)	(0.11)
GRGL(t-1)	0.035	0.093	0.001	0.057	0.027	0.051	0.045	0.036
	(0.09)	(0.14)	(0.08)	(0.11)	(0.08)	(0.10)	(0.07)	(0.12)
RWA_TA(t-1)	0.038	-0.016	0.130	0.071	0.190*	0.147	0.206*	0.147
	(0.17)	(0.25)	(0.12)	(0.17)	(0.09)	(0.12)	(0.11)	(0.15)
Ln_TA(t-1)	-0.158*	-0.056	-0.011	-0.010	-0.004	-0.007	-0.006	-0.007
	(0.08)	(0.12)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
GL_TA(t-1)	0.062	-0.302	0.132	-0.302*	-0.008	-0.392**	0.000	-0.385**
	(0.20)	(0.30)	(0.12)	(0.17)	(0.14)	(0.16)	(0.11)	(0.15)
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	198	198	198	198	198	198	198	198
R-squared within	0.3897	0.5288	0.3645	0.5244	0.2410	0.3896	-	-
R-squared between	0.0456	0.0510	0.0677	0.1374	-	-	-	-
R-squared overall	0.0511	0.2488	0.2197	0.3823	-	-	-	-
Number of SNLkey	41	41	41	41	-	-	41	41
AR(1)	-	-	-	-	-	-	0.4016	0.1987

Note: Table reports results of Fixed effects, Random effects, Pooled OLS (with clustered standard errors) and GLS estimator methods as robustness checks. The robust standard errors are reported in brackets. The table reports the results referring to the decrease of UTP, both in positive and negative terms. The dependent variables are the flows from UTP to performing loans (PL) and the flows from UTP to other non performing loans (NPL). The explanatory variables are: the flows from UTP to performing loans (Out-flow_PL); the flows from UTP to other categories of NPL (Out-flow_NPL); the category variable is equal to 1 if bank states in the balance-sheet report that the problem loans are managed by the legal office or by another office not specific in managing NPL; 2 if

there is a specific office that aims to recover non performing loans and if bank adopts an external office (e.g. cooperative banks); 3 if bank has a specific non core unit to manage NPL; 0 if bank does not explain in the balance-sheet how NPL are managed (MANAGE); and finally the loan loss provisions for UTP over gross loans (PROVISIONS). The capitalization measures are as follows: (Tier1 ratio); the profitability ratios, respectively the return on average equity (ROAE); the growth of gross loans (GRGL); the cost to income ratio (COST_INCOME); the proxy of business model measured by gross loans over total assets (GL_TA); the risk weight assets density (RWA_TA); the size measured by the natural logarithm of total assets (ln_TA) . All variables are at time t-1. The asterisks denote respectively significance at: *** p<0.01, ** p<0.05, * p<0.10

Table A1. Italian banking system loan breakdown – December 2016

	Gross (EUR mn)	Net (EUR mn)
Customer loans	1,828	1,656
Performing loans	1,503	1,494
Non-performing loans	325	162
- **Bad loans**	201	76
- **Unlikely-to-pay loans**	117	81
- **Past-due**	7	5

Source: Bank of Italy, ABN AMRO Group Economics

Appendix A

UTP exposures are analyzed separately from other categories of NPL for the following reasons:

- The average expected rate of losses differs widely between classes of impaired loans. Bank of Italy data show that it is above 68% for bad loans, 37.8% for UTP and around 22% for past due exposures (Bank of Italy, 2018). This is confirmed by the different levels of provision allocated by banks for each category of loan;
- Unlike European bad loan markets, the UTP market is relatively new, and limited in terms of volumes and number of transactions. Specific platforms and financial institutions dedicated to sales and securitizations of UTP loans are currently being set up on the European market (PWC, 2018).

This study is focused on the Italian banking system. Excluding the three countries which received financial assistance from the EU (Greece, Cyprus, and Portugal), Italy has the highest NPL ratio in the EU. In June 2018, this ratio was just under 10%, and considering the stocks, around one third of EU non-performing exposure was attributable to Italian banks (EBA, 2018). A high amount of Italian NPL are related to UTP. The weight of these exposures has varied from around 35% to 40% of the total impaired gross loans, as shown in Figure A1.

[Figure A1 approximately here]

In mid-2018, UTP exposures amounted to € 86 billion, of which 78% is concentrated in the ten largest Italian banks. In terms of loan loss provisions, the coverage ratio for bad loans and UTP is extremely different. For the Top 10 Italian banks, bad loan coverage reached 65.8% in June 2018, compared to 35.0% for UTP (PWC, 2018). The net book value of loans shows that the weight of UTP on total loans is even higher than bad loans. In other words, UTP appear to be the largest category of impaired loans if considered at net book value rather than gross book value.

Table A1 shows that, in terms of net value, the UTP portfolio accounts for more than a half of the total NPL.

Table A1 approximately here

Looking at the flows, in 2016, 57% of UTP remained UTP, 12% became collection, 5% returned to performing loans and 21% became bad loans. In general, about one fifth of the total UTP become bad loans each year, which is a cost for banks and poses systemic risks for the whole financial system (Bank of Italy, 2017).

Given the importance of UTP exposure in Italy, the country can be taken almost as a case study for focusing on the topic. The high level of disclosure of UTP loans among Italian banks also makes Italy a suitable topic of study. Although the new definition of NPL is adopted by all banks in the European Union, the balance-sheet data of Italian banks were in fact more complete and more detailed than those in other European countries in the analyzed period[vii]. This allows us to collect data on the stock of UTP, as well as data on the new annual flows of UTP and the flows of UTP that become performing again, or shift category of NPL. Moreover, it is important to note that in the past the definition of NPL differed across the European banking system. The European Banking Authority, in collaboration with the European Central Bank, issued a new definition of NPL in order to standardize the system only at the end of 2013. Focusing only on one country, such as Italy, it is possible to avoid any potential problems regarding data comparison. This study is thus able to focus on a homogeneous sample of financial institutions, and a homogeneous sample of impaired loans. However, because a

high proportion of European NPL are Italian exposures, our findings are relevant for the overall problem of NPL in Europe.

[i] NPL can be distinguished according to their level of deterioration, following the EBA (2014) definitions: "*Bad loans are exposures to debtors that are insolvent or in substantially similar circumstances.Unlikely-to-pay exposures (aside from those included among bad loans) are those in respect of which banks believe the debtors are unlikely to meet their contractual obligations in full unless action such as the enforcement of guarantees is taken. Overdrawn and/or past-due exposures (aside from those classified among bad loans and unlikely-to-pay exposures) are those that are overdrawn and/or past-due by more than 90 days and for above a predefined amount.*"

[ii] Although the literature focuses on NPL, we do not consider NPL exposures in comparing UTP behavior, because NPL in fact include UTP. Neither do we consider past dues as a term of comparison for UTP, because they are the starting point of deterioration and their weight in bank impaired portfolios is currently very low, as shown in Figure A1.

[iii] This sample includes both parent banks and subsidiaries, very small banks, and investment and wholesale banks.

[iv] A lower ratio of customer loans to total assets is used to identify universal banks.

[v] Banks more oriented to loans that differ from the other business models more oriented to wholesale and investment activities.

[vi] The data are collected from the yearly balance-sheet, and specific information on the single loans and borrowers is not available. More information on how data appears on bank balance sheets is given in Table 1.

[vii] Italian banking groups are obliged to include a specific section on Impaired exposures in their Annual Report, among the Notes to the Balance Sheet, providing data on risks and risk management policies. In detail, this section (*Table A.1.7 Banking Group – Balance sheet exposure to customers: change in gross non-performing loans*) includes data on UTP, showing gross initial and final exposures, together with the annual increases (transfers from performing loans, transfers from other impaired loans, other increases), as well as the annual decreases (transfers to performing loans, write-offs, collections, amounts realised upon disposal of positions, losses from disposal, and transfers to other categories of impaired exposure, other decreases). Banking groups in other European countries are not obliged to provide this information, and few thus present information on the structure of the non-performing credit portfolio in the same detail as Italian banks. In their Management report, other European banks usually include in the Section Risk and Capital Performance – Asset Quality, only stock values of the main credit exposure classes, categorised for example by business division, industry sector, geographical region, and creditworthiness categories of counterparties, or the flow values for the whole class of NPL (*Table: Development of impaired loans),* without details of credit categories.