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SECURITIZATION AND CREDIT QUALITY

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Securitization and Credit Quality[*]

Abstract

Banks are usually better informed on the loans they originate than other financial intermediaries. As a result, securitized loans might be of lower credit quality than — otherwise similar — non-securitized loans. We assess the effect of securitization activity on credit quality employing a uniquely detailed dataset from the euro-denominated syndicated loan market. We find that, at issuance, banks do not select and securitize loans of lower credit quality. Following securitization, however, the credit quality of borrowers whose loans are securitized deteriorates by more than those in the control group. We find tentative evidence suggesting that poorer performance by securitized loans might be linked to banks' reduced monitoring incentives.

Keywords: Securitization; syndicated loans; credit risk
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1. Introduction

Banks generate proprietary information and tend to have superior knowledge on the credit quality of the loans they originate. As a result, banks might have an incentive to securitize loans of lower credit quality to unsuspecting investors (Gorton and Pennacchi, 1995). Largely for this reason, securitization has been perceived as a major contributing factor to the 2007-2009 financial crisis (Financial Crisis Inquiry Commission, 2011). Following the crisis, a number of banks have been investigated by authorities over claims related to mis-sold securitized loans.[1]

In this direction, most of the empirical evidence suggests that banks tend to securitize the riskier mortgages of their portfolio (see for instance Krainer and Laderman, 2014; Elul, 2015). Simultaneously, some of the recent results — for the corporate bond market and for the mortgage market outside the United States (U.S.) — question whether securitized were necessarily riskier than non-securitized loans (see for instance, Benmelech et al., 2012; Albertazzi et al., 2015). Mainly due to data limitations however, most of the existing evidence is limited to the U.S. and focuses on the mortgage markets.

We assess the credit quality of securitized loans on the euro-denominated corporate loan market. In practical terms, we contrast the credit performance of securitized versus non-securitized loans over time. We first link the probability of loan securitization to a set of loan and borrower characteristics. We then track changes in loans' credit quality as measured by

[1] For instance, in the U.S., JP Morgan and Bank of America agreed to pay USD 4.5 and 9.1 billion, respectively, to settle court cases with institutional investors regarding mis-sold mortgage-backed securities (MBS). The U.S. Federal Housing Finance Agency reached settlements of around USD 16.5 billion with eighteen major financial institutions alleged to be involved in securities law violations and fraud in the sale of MBS to Fannie Mae and Freddie Mac. On a separate case, Citigroup and JP Morgan Chase agreed to pay around USD 15 billion to the U.S. Department of Justice over allegations related to misled investors on MBS during the time leading up to the 2007-2009 crises.

borrowers' expected default frequencies. In the robustness checks we also employ alternative methodologies, including propensity score matching, to compare the credit risk of securitized and non-securitized corporate loans which were, prior to securitization, very similar in terms of their observable characteristics.

We resort to a unique dataset obtained directly from securitization trustees operating in the European Union (EU). We construct this dataset by getting access to the portfolios of the majority of euro-denominated collateralized loan obligations (CLOs) so we are able to form a representative picture of the market, which includes public as well as private deals. Our detailed loan level dataset allows us to distinguish among all syndicated loans, those that were eventually securitized.

We focus on the euro-denominated CLO market which, we believe, is a good laboratory to assess the impact of securitization on credit quality. One reason is that in Europe the advent of securitization has been largely due to private market forces. The institutional setting for securitization markets in Europe stands in stark opposition to the U.S., where government sponsored enterprises have influenced the incentives and dynamics of securitization markets. In addition, in Europe the securitization markets started very timidly in the late 1990s, and developed significantly only from 2004 to 2007. In contrast, in the U.S. the introduction and growth of securitization markets have been much more continuous over time. The sudden appearance of securitization in Europe probably allows for a clearer assessment of its effects than in other regions. Finally, securitization activity in the Europe coexists with a very large covered bond market which provide banks with a source of long-term market funding alternative to securitization. Hence the differentiated effect of securitization, as opposed to other types of bank funding, can be more easily analyzed in Europe.

Concentrating on corporate loan securitization also provides a useful perspective as most of the existing literature analyzes the mortgage market. Mortgage lending, tends to be relatively mechanical and the credit risk of mortgage backed securities (MBS) is heavily reliant on housing prices. In contrast, corporate lending decisions are more dependent on idiosyncratic, and often proprietary, information on the credit quality of borrowers which is often obtained over time via lending relationships. In other words, information asymmetries are likely to be particularly pronounced in the securitization of corporate loans as the idiosyncratic risk of individual borrowers — which is often difficult to ascertain for outside investors — plays a large role. As a result, the screening and monitoring by the lender of individual borrowers would be expected to have a bigger impact on the performance of corporate loans after securitization than for other types of loans. We find that, based on borrowers' publicly available information at issuance, originating banks do not seem to select and securitize lower quality corporate loans to outsiders. At the same time, we also find that following securitization, the credit quality of borrowers whose loans are securitized deteriorates by more than those in the control group. While this underperformance could be due to a number of causes, we show some tentative evidence suggesting that the poorer performance of securitized loans might be linked to banks' reduced incentives to monitor those loans.

The remainder of the paper is organized as follows: Section 2 briefly reviews and draws hypotheses from the related literature. Section 3 describes the data sources and explains the empirical methodology used in the analysis. The results of estimations are presented and discussed in Section 4. Section 5 concludes.

2. Literature and Hypotheses

Studies for the U.S. suggest that banks that resorted more intensively to securitization activity in the years prior to the crisis relaxed their lending standards more aggressively than other institutions (Keys et al., 2011; Dell'Ariccia, 2012; Nadauld and Weisbach, 2012). There is also evidence linking securitization activity and increases in bank risk-taking (Goderis et al., 2007; Instefjord, 2005; Haensel and Krahnen, 2007), and augmented systemic risk (Michalak and Uhde, 2013; Krahnen and Wilde, 2008; Brunnermeier and Sannikov 2014; Wagner, 2007).[2]

In contrast, other studies do not find evidence suggesting that securitization led to riskier lending activities (Shivdasani and Wang, 2011 for leveraged buyouts; Casu et al., 2013 for overall bank risk; Albertazzi et al., 2015 for the Italian market). There is also an alternative literature that underlines the potential benefits of securitization suggesting that it supports financial stability by smoothing out risks among many investors (Duffie, 2008), improving banks' ability to manage credit risk (Cebenoyan and Strahan, 2004) and increasing banks' profitability (Jiangli et al., 2007).

More closely related to our paper, some of the empirical work examines the performance of loans after they have been securitized although evidence is limited and, at times, inconclusive. Some of these studies suggest that in the U.S. the credit quality of securitized corporate loans is not of worse than that of non-securitized loans (Benmelech et al., 2012).[3] Alternatively there is also evidence that finds inferior credit performance for securitized loans after securitization (Bord and Santos, 2015). For the mortgage market, recent results suggest that in the U.S. banks securitized ex-ante their riskiest mortgages and that following securitization the delinquency

[2] There is also evidence showing that securitization inhibits distressed borrowers' loan renegotiations (Piskorski et al., 2010).
[3] Authors report some evidence of under-performance for securitized loans originated between 2005 and 2007 although they suggest that this finding is not consistent across samples, performance measures, and horizons.

rates for securitized were higher than for non-securitized mortgages (Krainer and Laderman, 2014; Elul, 2015). On the other hand, looking at earlier period, Ambrose et al., (2005) show that in the U.S. securitized mortgages experienced lower ex-post defaults than those retained by banks' in their balance sheets.

We analyze whether banks securitized their lower quality euro-denominated corporate loans in the build up to the 2007-2009 financial crisis. Information asymmetries on the credit quality of borrowers between originating banks and purchasers of CLOs provide banks with the initial opportunity to do so as originators are likely to have more information about the borrowers than the buyers of the CLOs: This is either because they have experience in lending to that sector, or because they have a lending relationship with the borrower that allows them to collect proprietary information over time. From an investor's perspective, a related argument is that even sophisticated investors might have neglected tail risks (Gennaioli et al., 2012).

The credit cycle is also likely to play a significant role: During good states of a credit cycle (i.e., upswing of the credit cycle), investors might be more willing to acquire riskier securities. It could also be that during credit expansions it is more difficult for investors to assess the true value of information intensive securities — such as CLOs —.[4] Building on the extensive literature on adverse selection (Akerlof, 1970), this idea suggests that credit booms intensify the incentives to invest in securities that are more difficult to evaluate (Dang et al., 2012; Santos, 2015) and that credit risk embedded in securitized loans changes significantly across the business cycle (Demyanyk and Van Hemert, 2011).

[4] There is, in fact, evidence suggesting that investors did not have accurate models for pricing securitized debt, particularly CDOs (Jarrow et al., 2007).

In stark contrast, other studies suggest that banks might also have an incentive to securitize only those loans that are of intrinsic better credit risk in order to *signal* the quality of the securities (Greenbaum and Thakor, 1987; DeMarzo, 2005; Instefjord, 2005). Banks may also have an incentive to securitize less risky loans thereby increasing their risk profile for a given level of capital (Calem and LaCour-Little, 2004). Maintaining their long-term reputational capital in the securitization market might induce banks to sell their loans of relatively better quality (Albertazzi et al., 2015). The *signaling* hypothesis would therefore suggests that based on observables at the time of issuance, originating banks would be securitizing those loans with lower credit risk. Hence our first hypothesis would suggest that:

H1. *Signaling* hypothesis: At issuance securitized corporate loans were of better credit quality than, otherwise similar, non-securitized loans.

After securitization, originating banks might have less incentives to monitor borrowers because loans are passed on to outside investors. As a result, over time securitized would perform worse than non-securitized loans as the originating bank might monitor securitized loans less intensively (Petersen and Rajan, 2002). Supporting this view, some studies associated loan sales and securitization to looser credit monitoring (Gorton and Pennacchi, 1995; Duffee and Zhou, 2001; Morrison, 2005; Parlour and Plantin, 2008; Chiesa, 2008; Kamstra et al., 2014; Wang and Xia, 2015). Hence, our second hypothesis:

H2. *Monitoring* hypothesis: Over time securitized corporate loans perform worse than non-securitized loans due to banks' reduced monitoring incentives.

Another possible explanation for the relative worse credit performance of securitized loans after securitization, may be that banks are able to exploit their information advantage. Banks may have to securitize apparently better loans, based on publicly observable characteristics, in order to signal quality while still exploiting their information advantage over outsiders. In fact, the *signaling* argument relies on the fact that outsiders could only and roughly assess the credit quality through observable indicators such as credit ratings. At the same time given their access to proprietary information, and compared to outsiders, banks may possess a more accurate view on the future performance of the loans they originated. Hence, banks would have an incentive to securitize those apparently good loans that they expect to perform worse compared to the expected path of performance that could be inferred by outsiders from the observable characteristics of borrowers at the time of securitization. For example, there is evidence from trading in the secondary market of mortgage-backed securities suggesting that, banks exploit their access to inside information (Drucker and Mayer, 2008) and that prior to securitization, mortgage lenders adversely selected higher prepayment risk mortgages (Agarwal et al., 2012). We derive the third hypothesis from this discussion:

H3. *Lemons* hypothesis: Over time securitized corporate loans perform worse than non-securitized loans due to banks' ability of exploiting their information advantage over outside investors.

To disentangle between the *monitoring* and *lemons* hypotheses, we track and compare the ex-post credit risk of loans that are securitized versus those which are non-securitized and examine the loans where bank monitoring may have a more significant bearing on borrowers' performance. We conjecture that collateralized loans, where assets are pledged to the bank by the borrower, do not require as much monitoring as uncollateralized loans (Bester, 1985; Cerqueiro et al., 2015). This is because the borrower, having her assets at stake, would be less likely to engage in risk-shifting behavior at the expense of the lender and therefore show a better performance. If the *lemons* hypothesis is true, we would expect that, after securitization, the performance of loans that are securitized would be worse compare to those similar loans that are not securitized. If the *monitoring* hypothesis holds, we would expect that following securitization uncollateralized loans to perform more poorly than similar collateralized loans.

3. Data and Methodology

3.1 Data

Data on syndicated loan deals is obtained from Dealogic-Loanware. It includes all euro-denominated syndicated loans granted by euro-area banks between 2004 and 2009 to non-financial corporations headquartered in the euro area. Data on securitization activity comes from Dealogic-Bondware and Standard & Poor's.[5] We limit our sample to funded and cash-flow (balance-sheet) CLOs issued by banks headquartered in the euro-area and exclude refinancing and loans granted to finance M&A activities. We add two additional fields to our dataset which allow us to identify among all syndicated loans, those that were eventually securitized. We do this by collecting loan-by-loan confidential information from all major European Trustees for loans issued between 2004 and 2009. Overall, 1,795 out of 4,652 syndicated loans extended during this period are subsequently securitized.[6]

We carefully match our database on syndicated loans with information on the expected probability of default (*EDF*) of each borrower underlying each syndicated loan from 2005 to 2010. The *EDF*, computed by Moody's KMV, is a forward-looking firm-specific measure of the actual probability of default calculated using a structural approach which builds on Merton's

[5] An advantage of using Bondware and Standard & Poor's as the source for securitization data is that the names of the originator, date of issuance and deal proceeds are all registered.

[6] We only consider loans securitized from 2004 and 2007 as during the financial crisis the public CLO market ground to a halt. For the purposes of this work we do not consider the CLOs constructed to obtain central bank liquidity during the crisis.

model to price corporate bond debt (Merton, 1974). The final *EDF* value, expressed as a percentage, represents the implied risk of default and is constructed by combining companies' financial statements with stock market information and a proprietary default database maintained by Moody's KMV. *EDF* developments are regularly used as an indicator by financial institutions, investors, central banks and regulators to monitor credit risks of borrowers assuming that *EDFs* track closely physical expectations of default. By matching our syndicated loan database to those borrowers for which an *EDF* measure is available reduces our sample only to those borrowers that are listed on the stock market.

3.2 Model and Variables

We first estimate a logistic model that links the probability of loan securitization to certain loan and borrower characteristics:

$$Pr(securitized_i = 1|\mathrm{X}) = \Phi(\alpha EDF + \delta\Delta EDF + L'\theta + Z'\gamma) \qquad (1)$$

Where *Pr* is the probability of securitization for loan *I* in the year following its issuance, Φ is the standard cumulative normal probability distribution, L is a set of variables controlling for loan characteristics, and Z is another set of variables controlling for other factors expected to impact of the probability of default. Loan characteristics include: *loan spread* (basis points), *loan size* (natural logarithm), *maturity* (years), presence of *guarantees, collateral, instrument type*, *loan purpose* (corporate use, capital structure, project finance, transport finance, corporate control and property finance). We also control for *industry* (construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport), *syndicate size* and *date of issuance*.

We track the change in *EDF* (ΔEDF) to proxy for the deterioration or improvement of borrowers' credit quality (henceforth performance) over time. Using this variable we examine the ex-post (i.e., after the loan has been securitized) performance of the loan controlling for observable characteristics at the time of loan origination. We use three alternative measures to calculate ΔEDF as follows:

1. ΔEDF_A accounts for the change in credit risk for three time periods (one, two and three years) following the year in which the loan is issued. For example, to calculate a 2-year forward ΔEDF_A for a loan issued in 2005, we take the difference in *EDF* values for that borrower by subtracting the average values of 2007 from 2005.

2. ΔEDF_B measures the differences in *EDF* between the year in which the loan is issued and three different time periods (i.e., 2008, 2009 and 2010) selected to take place during the financial crisis. For example, assume that loan *A* is issued in 2005 and loan *B* is issued in 2006, to compute the average ΔEDF_B for year 2008 for loan *A*, we take the difference between the *EDF* in 2008 and 2005. For loan *B*, we take the difference in *EDF* between 2008 and 2006. This alternative measure allows us to look at the change in *EDF* from the time of securitization to different stages of the financial crisis.

3. ΔEDF_C measures the change in borrowers' during the financial crisis. To account for this, we incorporate the ΔEDF for each borrower calculated as changes in *EDF* from the start of the financial crisis (third quarter of 2007) to three separate periods of the financial crisis (i.e., 2008, 2009 and 2010). For example, to calculate the ΔEDF_C for

2008, we take the difference between the average *EDF* in 2008 and that of the third quarter of 2007. The idea is that many of the inherent risks in a securitization structure could be of systemic nature and materialize only in the event of a (large) financial crisis.

3.3 Propensity Score Matching

The analysis of the effect of securitization on loan's credit quality might raise self-selection concerns with regard to the decision to securitize certain loans. If credit performance of securitized and non-securitized loans would have differed systematically in the absence of securitization, comparing credit risk of securitized and non-securitized loans might yield biased estimates on the impact of securitization. Under this assumption, if securitized loans are found to perform differently, on average, than non-securitized, the difference may be due to the effect of self-selection rather than to securitization. Strictly speaking in order to test our hypothesis, we need to know what would have happened to the credit quality of securitized loans had they had not been securitized. Because it is impossible to observe the same loan in both states, we need to find an appropriate proxy for the counterfactual performance of securitized loans. Good candidates for the counterfactual are non-securitized loans from which we construct our control group. We construct this control group using a propensity score matching (PSM) approach (Rosenbaum and Rubin, 1983). PSM allows us reduce the matching problem to a single dimension via the propensity score.

We match our loan sample using propensity scores to compare securitized and non-securitized loans which are ex-ante (i.e., prior to securitization) similar in terms of some of their key observable characteristics. Importantly our control group — constructed from the non-securitized loans — is selected among those loans whose credit risk trajectory prior to securitization lies as close as possible to that of similar securitized loans. If we assume that there are no significant differences in unobservables between the two matched groups of loans — or that unobservables do not play a significant role on the potential outcome— the observed differential in performance (ΔEDF) can be attributed to the effect of having received the treatment, which in our setting is the securitization of the loan.

Through matching we restrict our inference to the sample of securitized and matched non-securitized loans. The impact of the treatment (securitization) on loan i, δ_i, is the difference between potential outcomes (ΔEDF) with and without treatment:

$$\delta_i = \Delta EDF_{1,i} - \Delta EDF_{0,i} \tag{2}$$

The impact of securitization over the sample would be the average treatment effect on the treated (ATT), computed as follows:

$$ATT = E(\Delta EDF_1 - \Delta EDF_0 | T = 1) \tag{3}$$

As indicated, the treated group (securitized loans, denoted $T_i = 1$ for loan i) is matched with a control group (non-securitized loans, denoted $T_i = 0$ for loan i) on the basis of its propensity score which is a function of loan and borrower observable characteristics:

$$P(X_i) = Pr(T_i = 1|X_i), with\ (0 < P(X_i) < 1) \tag{4}$$

In our setting the propensity score, $P(X_i)$, is initially estimated with a probit model where the binary dependent variable has a value of one for securitized loans, and zero otherwise. The regressors, X_i include credit quality prior to securitization, loan characteristics — loan purpose, business industry and size — as well as bank, year and country dummies.

There needs to be sufficient overlap in the propensity scores to match securitized and non-securitized loans. We impose a common support condition $[(0 < P(X_i) < 1)]$ that restricts inference to treated and non-treated units with comparable propensity scores. That is, non-treated units whose propensity scores are lower (or higher) than the defined minimum (maximum) are dropped. We employ nearest-neighbor matching where each securitized loan is matched with those non-securitized loans with the closest propensity scores (Dehejia and Wahba, 2002):

$$C(i) = \min\left|p_i - p_j\right| \tag{5}$$

where by $C(i)$ is the set of control loans with an estimated value of the propensity score p_i, matched to securitized loan i. We calculate our control group using matching with and without replacement.[7] This allows us to increase the quality of the matching and decrease bias (Dehejia and Wahba, 2002). Our main results are constructed using one to one (1:1) matching where each securitized loan is matched with a single non-securitized loan. We also calculate results for two (1:2) and four (1:4) matches. Increasing the number of matches might also increase bias — as the second and fourth closest matches are usually further away from the treated loan than the first match. At the same time the use of multiple matches can decrease variance as the matched sample becomes larger (Rubin and Thomas, 2000).

4. Results

Descriptive statistics are presented in Table 1. In Panel A we display the mean, median, standard deviation and mean comparison (t-tests) of loan and borrower characteristics. We find that securitized loans tend to be smaller in size and have a longer maturity than non-securitized loans. The number of banks in the loan syndicate and the ratio of banks active in securitization (to total banks) in the syndicate are almost identical for both groups. *EDFs* of companies whose loans are non-securitized are usually higher than for companies whose loans are securitized. In Panel B we

[7] In the latter case a non-securitized loan can be used as a match more than once

display the summary statistics for the dummy variables. We find that a large share of securitized loans are secured using collateral and tend to be leveraged.

4.1 Whole Sample

In Table 2 we present the results for the logistic model including the levels (*EDF*) and changes (ΔEDF_A) in credit risk. We start by employing only the level of credit risk (i.e., *EDF*) at the time of the issuance (column I). Controlling for a set of micro and macro variables,[8] we find that the *EDF* coefficient is negatively affected by the probability of loan securitization. This suggests that loans of borrowers with relatively higher default risk are less likely to be securitized. The finding supports the *signaling* hypothesis that suggests that banks signal quality by retaining assets of poorer credit risk, as observed at issuance, and tend to securitize assets of initially better credit quality (Greenbaum and Thakor, 1987; DeMarzo, 2005; Instefjord, 2005).

Subsequently, we relate the ex-post performance of borrowers (ΔEDF_A) to the likelihood of loan securitization. Columns II to IV show the ΔEDF_A for sets of one to three year time periods following loan securitization during that year. We report a positive relationship between the ex-post ΔEDF_A and the probability of loan securitization for all time horizons. This suggests that the likelihood of loan securitization is higher for borrowers that showed worse performance.

We present the ΔEDF_B results in Table 3. Here we measure the differences in *EDF* between the year in which the loan issued and three time periods (i.e., 2008, 2009 or 2010) chosen to take place during the financial crisis. We find that the coefficient of the ΔEDF_B is significant for all time horizons and suggests that borrowers whose loans are securitized showed inferior performance than loans that were not.

[8] Note that summary statistics on these variables are not reported to keep the tables parsimonious. All these statistics are available upon request.

We are also interested in changes in borrowers' relative performance during the financial crisis (ΔEDF_C). ΔEDF_C is calculated as the changes in *EDF* from the start of the financial crisis to three separate periods that take place during the financial crisis. Results — presented in Table 4 — show that ΔEDF_C has a positive and significant coefficient for the 2009 and 2010 periods and is not significant for 2008. This suggests that loans of borrowers whose default risk would materialized in the event of a systemic crisis were more likely to be securitized.

4.2 Propensity scores

As an alternative strategy to assess the robustness of our results we use a propensity score matching. This technique allows us measure the impact of securitization on credit risk using a comparable sample of loans.

To verify the quality of matching graphically we first plot the distribution of the propensity score for both groups (securitized or non-securitized loans), before and after matching, for the whole sample (Figure 1). In the unmatched sample, the propensity score distribution of the non-securitized loans is skewed to the left. In contrast in the matched sample the distribution of the two groups is similar. This suggests that the use of propensity score matching is appropriate in our context.

Table 5 presents the ΔEDF_A results. We find that for loans of the securitized (treatment) group, the treatment has increased their future *EDF* for all time horizons and that the highest impact is seen in year three. It shows that the credit quality of borrowers whose loans are securitized deteriorates significantly in comparison to the control group.

The highest impact is observed after three years as suggested by the coefficients for the average treatment of the treated (*ATT*). This seems a plausible result as we are looking at loans that already have an observable credit risk indicator (i.e., *EDF*). For such loans one would expect that the change in credit quality would take time as outsiders (such as CLO investors) can already assess the initial credit risk as assessed by financial markets via *EDF*s. In other words, the effect of banks' informational advantage over outsiders would not surface completely in the short-term and would materialize gradually over time.

Table 6 presents *ATT*s results for $\Delta EDF_{B.}$ We find that only ΔEDF_B for year 2008 is significant. The finding captures the dramatic shift in borrowers' *EDF* values immediately after the start of the financial crisis in 2008. As a result of the financial crisis a significant increase was observed in credit risk in 2008 across the board for all types of borrowers. The results show that this change was larger for companies whose loans were securitized in line with our earlier findings. Our results are also robust when two and four matches are used. We present *ATT*s for ΔEDF_C in Table 7. In line with the results above securitized loans performed worse in the post-crisis period, although only the difference in *EDF* between 2008 and the beginning of the crisis is statistically significant.

Thus far our results suggest that loans of borrowers with relatively higher default risk are less likely to be securitized, supporting the *signaling* hypothesis. We also show that borrowers of securitized loans performed more poorly than borrowers of non-securitized loans. There may be two ways to explain these findings. It could be that banks may be exploiting the informational advantage that they have over outsiders. That is, banks might be better able to predict more accurately future performance of the loans and keep as a result the better ones (i.e., *lemons* hypothesis). Alternatively, securitized loans may be performing more poorly due to banks' weaker incentives to carefully monitor borrowers (i.e., *monitoring* hypothesis). We test these arguments by examining the performance of borrowers whose loans are more reliant on bank monitoring. While it is difficult to disentangle between these two hypotheses, we can provide some evidence in this direction: We hypothesize that collateralized loans, where assets are pledged against the loan by the borrower, do not require as much monitoring as uncollateralized loans. This is because the borrower, having their assets at stake, would be more vigilant about their performance.

4.3 Collateralized versus Uncollateralized Loans

We repeat our analysis and distinguish between those corporate loans requiring and not requiring collateral. Results for logit models for all three versions of ΔEDF are presented in Table 8. For ΔEDF_A we do not find any significant coefficients for the collateralized loans group (columns I-III). Conversely, in the uncollateralized group, ΔEDF_A is positive and statistically significant for all time horizons (columns X to XII). For uncollateralized loans the likelihood of a loan being securitized is higher if the borrower performed poorly after issuance. Results for ΔEDF_B are presented for collateralized (columns IV-VI) and uncollateralized (columns XIII-XV) loans respectively. For all time horizons of ΔEDF_B, the results show that securitized loans borrowers were more likely to perform more poorly. We also observe significant negative coefficients for collateralized loans for the years 2009 and 2010. These results provides some, albeit weaker, evidence that banks kept the collateralized loans that are expected to show an inferior performance in their books rather than securitizing them. Results for ΔEDF_C are shown in columns VII-XI, for collateralized, and XVI-XVIII, for uncollateralized loans. For uncollateralized loans we find significant and positive coefficients for 2009 and 2010. Overall, Table 8 provides tentative evidence suggesting that among securitized borrowers, the *EDF* of borrowers whose loans were not collateralized increased significantly by more compared to borrowers whose loans were collateralized.

In Table 9 we present the results for propensity score matched estimations for the two sub-groups. We find that none of the coefficients for the ΔEDF ($_{A}$, $_{B}$ or $_{C}$) variables are significant for loans that are collateralized. For the uncollateralized sample, coefficients of *ATT* are statistically significant and positively related to the probability of securitization only for $\Delta EDF_{\mathbf{A}}$ variables. It is worthwhile to note that for $\Delta EDF_{\mathbf{A}}$, *ATT* increases over time where the largest difference is reported Year 3. In other words the difference becomes more prevalent in the long-term as the effects of banks' reduced monitoring of the borrower gradually start influencing corporates' performance. These findings provide indirect evidence for the *monitoring* hypothesis. Banks, having sold the loan to third parties, might may be less interested in monitoring the borrower which in turn, may have affected the borrower's performance. This interpretation is driven by the fact that we observe more deterioration in credit quality for uncollateralized loans that are securitized.

5. Conclusions

We examine the relative performance of corporate borrowers whose loans were securitized in Europe during the period preceding the financial crisis. We find that banks do not seem to have selected and securitized loans of lower quality to outsiders, providing evidence consistent with the *signaling* argument. Banks seem to have kept poorer quality corporate loans to signal the quality of the securitized assets to the investors. We also show that following securitization, the credit quality of borrowers whose loans are securitized deteriorated significantly over time compared to the control group. We find that poor performance is possibly linked to the weakening in monitoring activities by banks after securitization as within securitized loans, non-collateralized ones, show worse performance than securitized ones.

In the post-crisis period, European policy makers, recognizing the potential benefits of securitization to the financial system, are considering policy options to transform and revive securitization markets in the EU (European Central Bank, 2014). Having a better understanding of the financial stability implications of securitization can help to develop a robust securitization market. Our results suggest that securitization might impact negatively on the credit quality of securitized loans over time. They also vouch for the advantages of setting up mechanisms to improve the information quality on the collateral pledged by borrowers. These might include credit registers with enhanced mark to market information on collateral values.

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Table 1

Descriptive Statistics

Panel A

Loan characteristics	Non-securitized (N=429) Mean	Median	Std. dev	Securitized (N=89) Mean	Median	Std. dev	Mean comparison t-values
Spread	138	87.5	160	310	275	181	-9.01***
Size (million Euro)	670	242	1,328	435	170	819	1.60
Maturity	5.8	5.6	2.1	8.1	8	1.4	-9.88***
Syndicate size	13.9	11	10.1	13.4	10	11.4	0.41
Securitization active banks	0.69	0.69	0.18	0.69	0.64	0.19	-0.00
EDF	0.41	0.08	1.31	0.17	0.05	0.31	1.72*

Panel B - Percentage of loans

	Non-securitized	Securitized
Secured	35.79%	52.85%
Subordinated	4.22%	17.99%
Sponsored	53.47%	97.02%
Instrument type		
Term loan	29.01%	14.64%
Term loan A	9.82%	16.13%
Term loan B	5.82%	28.54%
Term loan C	4.19%	26.18%
Revolving credit	29.80%	4.34%
Credit facility	12.82%	0.12%
Other	8.54%	10.05%
Risk and credit ratings		
Leveraged	53.82%	98.88%
Investment grade	45.51%	1.12%
Highly leveraged	0.67%	0.00%
Borrower industry		
Industrial	80.36%	92.06%
Bank and Financial	8.54%	1.86%
Utility	4.76%	1.36%
Other	6.33%	4.71%
Rated	12.79%	6.45%

Table 2

Probability of loan securitization and change in default risk after loan issuance

This table presents coefficient estimates for logit regressions estimating the probability of loan securitization within one year of loan issuance. *EDF* is the expected default frequency, computed by Moody's KMV, at the time of loan issuance. ΔEDF_A are changes in borrower credit quality to a certain period after issuance. For example if the loan is issued in 2005 then ΔEDF_A within 1 year of the borrower equals the *EDF* in 2006 minus the *EDF* in 2005 divided by *EDF* in 2005. We control for observable loan and syndicate characteristics at the time of loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, loan rating, type of loan and if the loan is leveraged. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Loan purpose is controlled for using dummy variables (categorized as general corporate use, capital structure, project finance, transport finance, corporate control and property finance). Business Industry is controlled for using dummy variables (categorized as construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport). Year dummy variables control for the macroeconomic conditions. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	I	II	III	IV
EDF	-0.636*	-0.915**	-1.220***	-0.907**
	(0.372)	(0.286)	(0.324)	(0.460)
ΔEDF_A *within*				
1 year		0.925*		
		(0.399)		
2 year			0.449***	
			(0.131)	
3 year				0.173***
				(0.052)
Controls for:				
Loan characteristics	Yes	Yes	Yes	Yes
Syndicate characteristics	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Business industry	Yes	Yes	Yes	Yes
Year dummy variables	Yes	Yes	Yes	Yes
Constant	-11.4***	-12.4***	-14.2***	-13.8***
	(1.700)	(1.879)	(2.094)	(2.054)
Number of observations	518	474	460	446
Pseudo R-squared	0.49	0.53	0.56	0.56

Table 3
Probability of loan securitization and change in default risk from issuance to different periods of the financial crisis

This table presents coefficient estimates for logit regressions estimating the probability of loan securitization within one year of loan issuance. *EDF* is the expected default frequency, computed by Moody's KMV, at the time of loan issuance. ΔEDF_B are changes in borrower credit quality from issuance to different periods of the financial crisis. For example if the loan is issued in 2006 then Δ *in* EDF_B from the loan issuance to 2008 equals the *EDF* in 2008 minus the *EDF* in 2006 divided by *EDF* in 2006. We control for observable loan and syndicate characteristics at the time of loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, if the loan is rated, type of loan and leveraged loan. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Loan purpose is controlled for using dummy variables (categorized as general corporate use, capital structure, project finance, transport finance, corporate control and property finance). Business industry is controlled for using dummy variables (categorized as construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport). Year dummy variables control for the macroeconomic conditions. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	I	II	III
EDF	-0.798*	-0.938*	-0.663**
	(0.437)	(0.521)	(0.311)
ΔEDF_B *from the loan issuance to*			
2008	0.246*		
	(0.142)		
2009		0.135***	
		(0.052)	
2010			0.092**
			(0.042)
Controls for:			
Loan characteristics	Yes	Yes	Yes
Syndicate characteristics	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes
Business industry	Yes	Yes	Yes
Year dummy variables	Yes	Yes	Yes
Constant	-13.262***	-14.131***	-14.096***
	(1.980)	(2.208)	(2.198)
Number of observations	446	417	428
Pseudo R-squared	0.55	0.58	0.58

Table 4

Probability of loan securitization and change in default risk during the financial crisis

This table presents coefficient estimates for logit regressions estimating the probability of loan securitization within one year of loan issuance. *EDF* is the expected default frequency, computed by Moody's KMV, at the time of the loan issuance. ΔEDF_C are changes in borrower credit quality during the financial crisis. We control for observable loan and syndicate characteristics at the time of the loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, if the loan is rated, type of loan and if the loan is leveraged. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Loan purpose is controlled for using dummy variables (categorized as general corporate use, capital structure, project finance, transport finance, corporate control and property finance). Business Industry is controlled for using dummy variables (categorized as construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport). Year dummy variables control for the macroeconomic conditions. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	I	II	III
EDF	-0.894*	-0.951*	-0.677*
	(0.498)	(0.544)	(0.319)
ΔEDF_C *from Q3:2007 to*			
2008	0.234		
	(0.156)		
2009		0.133**	
		(0.051)	
2010			0.092*
			(0.042)
Controls for:			
Loan characteristics	Yes	Yes	Yes
Syndicate characteristics	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes
Business industry	Yes	Yes	Yes
Year dummy variables	Yes	Yes	Yes
Constant	-13.2***	-14.1***	-14.0***
	(1.989)	(2.214)	(2.204)
No of observations	444	412	423
Pseudo R-squared	0.54	0.57	0.58

Figure 1
Distribution of propensity score of securitized and non-securitized loans before and after matching

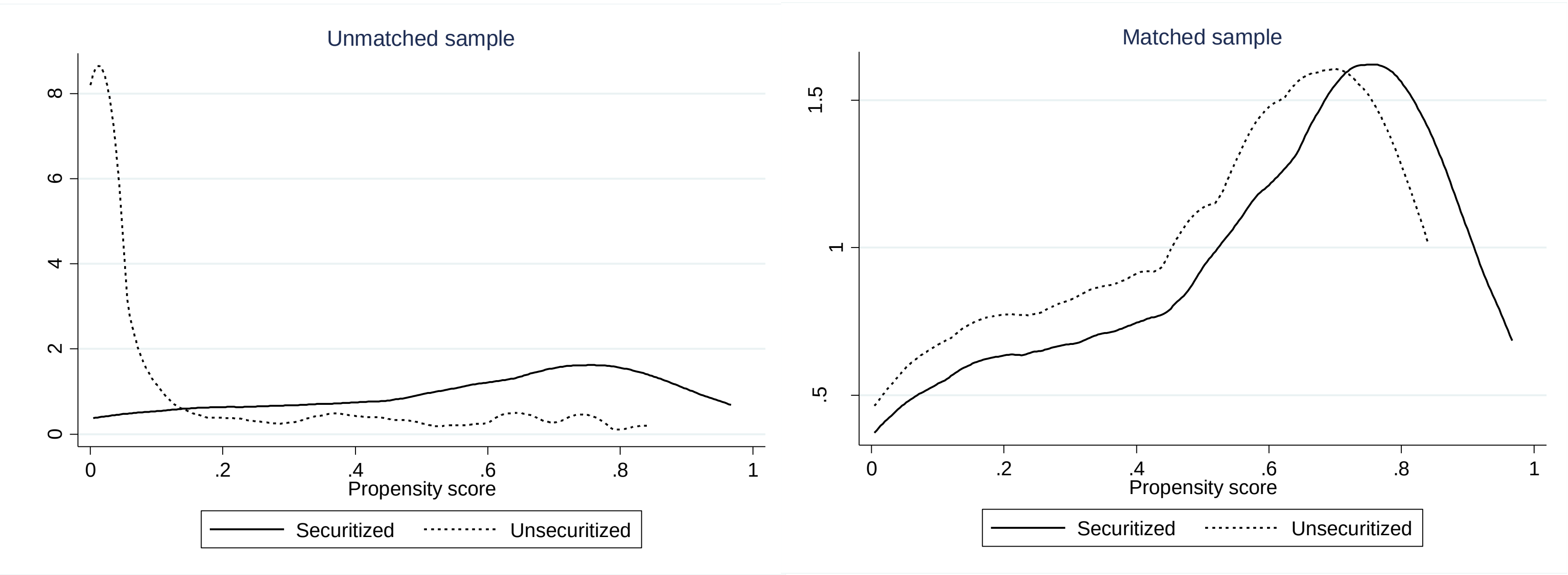

Table 5

Change in default risk after loan issuance for securitized (treatment) versus non-securitized loans using with propensity score matching

The table reports the average treatment effect on the treated (*ATT*). It shows propensity score matching estimates of the average treatment effect of securitization on default risk, ΔEDF_A, of the securitized loans. The average treatment effect of securitization on ΔEDF is estimated as the difference between securitized loans' mean ΔEDF and that of matched non-securitized loans. ΔEDF_A proxies for the deterioration or improvement of the borrower credit quality over time to assess the ex-post performance of the borrower of the loan. For example if the loan is issued in 2005 then ΔEDF within 1 year of the borrower equals the *EDF* in 2006 minus the *EDF* in 2005 divided by *EDF* in 2005. Robust standard errors are bootstrapped and presented in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Number of matched controls			
	One	Two	Four	Number of observations
ΔEDF_A *within*				
1 year	0.218**	0.206**	0.168*	474
	(0.102)	(0.094)	(0.095)	
2 year	0.792**	0.834**	0.892**	460
	(0.403)	(0.369)	(0.398)	
3 year	2.328***	2.007**	1.984**	446
	(0.866)	(0.986)	(0.814)	

Table 6

Change in default risk from issuance to different periods of the financial crisis for securitized (treatment) versus non-securitized loans using propensity score matching

The table reports the average treatment effect on the treated (*ATT*). It shows propensity score matching estimates of the average treatment effect of securitization on the performance, ΔEDF_B, of the securitized loans. The average treatment effect of securitization on ΔEDF_B is estimated as the difference between securitized loans' mean ΔEDF_B and that of matched non-securitized loans. ΔEDF proxies for the deterioration or improvement of the borrower credit quality over time to assess the ex-post performance of the borrower of the loan. For example if the loan is issued in 2006 then ΔEDF from the loan issuance to 2008 equals the *EDF* in 2008 minus the *EDF* in 2006 divided by *EDF* in 2006. Robust standard errors are bootstrapped and presented in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Number of matched controls			
	One	Two	Four	Number of observations
ΔEDF_B *from issuance to*				
2008	0.654*	0.490*	0.477**	446
	(0.351)	(0.299)	(0.210)	
2009	1.286	1.588	1.646	417
	(1.313)	(1.363)	(1.048)	
2010	2.049	1.851	1.742	428
	(1.536)	(1.446)	(1.571)	

Table 7

Change in default risk during the financial crisis for securitized (treatment) versus non-securitized loans using propensity score matching

The table reports the average treatment effect on the treated (*ATT*). It shows propensity score matching estimates of the average treatment effect of securitization on the default risk, ΔEDF_C, of the securitized loans. The average treatment effect of securitization on ΔEDF_C is estimated as the difference between securitized loans' mean ΔEDF and that of matched non-securitized loans. ΔEDF_C proxies for the deterioration or improvement of the borrower credit quality from the start of the financial crisis (Q3:2007) to three different periods of the financial crisis. The objective is to measure relative changes in default risk during the crisis. Robust standard errors are bootstrapped and presented in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Number of matched controls			
	One	Two	Four	Number of observations
ΔEDF_C *from Q3:2007 to*				
2008	0.522**	0.405*	0.371*	444
	(0.262)	(0.255)	(0.257)	
2009	1.604	1.490	1.581	412
	(1.317)	(0.999)	(1.218)	
2010	1.204	1.797	1.675	423
	(0.486)	(1.589)	(1.408)	

Table 8

Monitoring incentives: Probability of loan securitization and change in default risk for collateralized and non-collateralized loans

This table presents coefficient estimates for logit regressions estimating the probability of loan securitization within one year of loan issuance. *EDF* is the expected default frequency, computed by Moody's KMV, at the time of the loan issuance. ΔEDF_A are changes in borrower credit quality to a certain period after issuance. ΔEDF_B are changes in borrower credit quality from issuance to different periods of the financial crisis. ΔEDF_C are changes in borrower credit quality during the financial crisis. We control for observable loan and syndicate characteristics at the time of the loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, if the loan is rated, type of loan and if the loan is leveraged. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Loan purpose is controlled for using dummy variables (categorized as general corporate use, capital structure, project finance, transport finance, corporate control and property finance). Business Industry is controlled for using dummy variables (categorized as construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport). Year dummy variables control for the macroeconomic conditions. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Collaterized loans									Uncollaterized loans								
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII
EDF	-1.45	-2.108	-13.510	-13.441	1.114	-0.251	-13.858	1.168	-0.251	-0.689	-1.067**	-0.293*	-0.689	-1.174	-0.491	-0.845	-1.254	-0.518
	(1.768)	(4.606)	(9.319)	(9.571)	(3.115)	(0.980)	(9.692)	(3.077)	(0.977)	(0.463)	(0.545)	(0.762)	(0.576)	(0.912)	(0.605)	(0.576)	(0.912)	(0.688)
ΔEDF_A *within*																		
1 year	0.906									1.867***								
	(2.769)									(0.558)								
2 year		0.446									1.326***							
		(0.632)									(0.354)							
3 year			0.188									0.481***						
			(0.162)									(0.125)						
ΔEDF_B *from issuence to*																		
2008				0.469									0.262*					
				(0.576)									(0.152)					
2009					-1.657*									0.246***				
					(0.964)									(0.078)				
2010						-0.685*									0.217***			
						(0.359)									(0.070)			
ΔEDF_C *from Q3:2007 to*																		
2008							0.531									0.247		
							(0.613)									(0.169)		
2009								-1.694									0.246***	
								(0.985)									(0.079)	
2010									-0.686*									0.217***
									(0.357)									(0.071)
Controls for:																		
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Syndicate characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	126	112	107	107	97	102	107	97	102	331	331	322	322	304	310	320	299	305
Pseudo R-squared	0.47	0.55	0.58	0.58	0.85	0.81	0.57	0.85	81	0.54	0.62	0.62	0.51	0.55	0.56	0.50	0.55	0.56

Table 9

Monitoring incentives: Change in default risk for collateralized and non-collateralized loans after loan issuance comparing securitized (treatment) versus non-securitized loans using propensity score matching

The table reports the average treatment effect on the treated (*ATT*). It shows propensity score matching estimates of the average treatment effect of securitization on the default risk, ΔEDF, of the securitized loans. The average treatment effect of securitization on a ΔEDF is estimated as the difference between securitized loans' mean ΔEDF and that of matched non-securitized loans. ΔEDF_A are changes in borrower credit quality to a certain period after issuance. For example if the loan is issued in 2005 then ΔEDF within 1 year equals the *EDF* in 2006 minus the *EDF* in 2005 divided by *EDF* in 2005. ΔEDF_B are changes in borrower credit quality from issuance to different periods of the financial crisis. For example if the loan is issued in 2006 then ΔEDF from the loan issuance to 2008 equals the *EDF* in 2008 minus the *EDF* in 2006 divided by *EDF* in 2006. ΔEDF_C are changes in borrower credit quality during the financial crisis. Robust standard errors are bootstrapped and presented in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Collateralized loans		Uncollateralized loans	
	ATT	Number of observations	*ATT*	Number of observations
ΔEDF_A *within*				
1 year	0.018	143	0.582**	331
	(0.037)		(0.248)	
2 year	0.094	129	1.688***	331
	(0.398)		(0.608)	
3 year	0.998	124	3.580*	322
	(1.637)		(1.870)	
ΔEDF_B *from issuance to*				
2008	0.321	124	0.351	322
	(0.391)		(0.552)	
2009	1.318	113	1.171	304
	(1.644)		(2.353)	
2010	2.165	118	2.417	310
	(3.151)		(2.051)	
ΔEDF_C *from Q3:2007 to*				
2008	0.309	124	0.224	320
	(0.299)		(0.789)	
2009	1.295	113	1.794	299
	(1.628)		(1.759)	
2010	2.141	118	3.157	305
	(1.845)		(3.141)	

References

(Bold, Times New Roman 10)

Reference Style:

Adopt the style of the Elesvier journal **Economics Letters**, which is one of the simplest.

Examples:

*Journal*s:

Krueger, A. B. and J. Maleckova, 2003, Education, poverty and terrorism: is there a connection?, Journal of Economic Perspectives 17, 119-144.

Books/Monographs:

Krueger, A.B., 2007, What Makes a Terrorist? Economics and the Roots of Terrorism. (Princeton University Press, Princeton, NJ).

Contributions to books:

Krueger, A.B. and D.D. Laitin, 2008, ‘Kto Kogo?: A cross-country study of the origins and targets of terrorism, in: P. Keefer and N. Loayza, eds., Terrorism, Economic Development, and Political Openness (Cambridge University Press, Cambridge) 148-173.