Páipéar Taighde Teicniúil
Research Technical Paper

14RT14

Property debt overhang: the case of Irish SMEs

Fergal McCann and Tara McIndoe-Calder

Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

Property debt overhang: the case of Irish SMEs

Fergal McCann[a] and Tara McIndoe-Calder[b*]
[a] Financial Stability Division, [b] Irish Economic Analysis Division
Central Bank of Ireland

October 2014

Abstract

The detrimental impacts of credit booms, property booms and firm over-leverage are well-established in a growing literature highlighting their effects on household consumption, firm investment and economic growth. The link between credit-fuelled property market booms and firms' ability to service their debts has however up to this point not been studied. Using a unique data set on the property and "core" enterprise debts of Irish Small and Medium Enterprises (SMEs) at December 2013, we highlight the extent to which Irish non-real-estate SMEs have borrowed for property investment purposes. We show that the existence of such property-related debts is a crucial determinant of the probability of SME loan default, suggesting a large property-related debt overhang for these firms. We extend the analysis by showing that the intensity of firms' property-related borrowings has an additional impact on the probability of loan default. In doing so, we highlight an additional channel through which credit-driven property booms can have long-lasting harmful effects on economic growth prospects.
Keywords: Property markets, SMEs, credit risk, firm leverage.

*E-mail: fergal.mccann@centralbank.ie; tara.mcindoecalder@centralbank.ie. We thank, in alphabetical order, Thomas Conefrey, Christian Danne, Edward Gaffney, Stefan Gerlach, Patrick Honohan, Robert Kelly, Gerard O'Reilly, Conor O'Toole and seminar participants in the Central Bank of Ireland Financial Stability Division and the ESRI Conference *Financing SMEs in Economic Recovery*, September 2014 for helpful discussions. The views presented in this paper are those of the authors alone and do not represent the official views of the Central Bank of Ireland or the ESCB. Any remaining errors are our own.

Non Technical Summary

The detrimental impact of credit and property boom-bust cycles on consumption and growth has received much high-profile attention in the aftermath of the global financial crisis (Mian et al., 2013; Dynan et al., 2012). Separately, an empirical literature on non-financial corporates has shown that debt overhang can negatively impact firm investment (Aivazian et al., 2005; Cai and Zhang, 2011; Coricelli et al., 2012).

Using a unique data set on the property and enterprise debts of Irish Small and Medium Enterprises (SMEs) at December 2013, we highlight the extent to which Irish non-real-estate SMEs have borrowed for property investment purposes, before showing the detrimental impact of these property-related borrowings on firms ability to repay their enterprise debts. These property-related borrowings represent an inefficient allocation of capital to projects outside a firm's set of core competencies, and highlight an additional channel through which credit-driven property booms can have long-lasting harmful effects on economic growth prospects. To the best of our knowledge, this is the first case in which firms property debt overhang can be identified and analysed.

Our data set covers the population of SME loans at three Irish banks, covering roughly 70 per cent of the total SME credit market. An SME is defined as having a property-related exposure if it has borrowing in a non-property-related sector (referred to as its "core activity"), while also having exposures located in the Buy-to-Let mortgage, personal investment or Commercial Real Estate portfolios of the same bank. We show that in some sectors the percentage of enterprise SME loans held by firms that also have property-related borrowing can reach close to 20 per cent, while when weighted by loan balance, the figure can reach 30 to 40 per cent, with the largest property exposures being in the Hotels and Restaurants, Wholesale and Retail, and Business and Administrative Services sectors.

We then examine the pernicious effects of SME property market speculation: these firms have higher default rates on their enterprise borrowing than firms with no property exposures. The pattern holds in all sectors of economic activity, with default rates among firms with property debts reaching 60 per cent in some cases.

We formalize the relationship between property borrowing and SME loan default by entering measures of both the existence and the intensity of firms property-related borrowing into a cross-sectional SME default model. In all cases, it is the default status of loans related to the core business activity of the firm, rather than the property-related loans of these firms, that are being modelled.

Finally, we construct a counter-factual observation for each SME loan with a property exposure to identify the effect of property borrowing on default using a Propensity Score Matching (PSM) model. The counter-factual observation for each SME loan with a property exposure is an SME loan in the data with similar observable characteristics, but without property debt. The PSM results in show that post-matching, SME loans with property exposure are more likely to default than those without property exposure.

The conclusions of the analysis should serve as a stark warning to policy makers in countries experiencing credit-fuelled property price increases. The data presented here suggest that firms and banks will act to allocate capital inefficiently from the productive to the property-related sector of the economy during a property boom. Complementing the literature on household debt overhang, we highlight an additional channel through which credit-fuelled property booms can impact post-crisis growth: firms may also subsequently experience difficulty in repaying their debts as a result of their over-extended property-related borrowings. Such a pattern can have long-run impacts by allocating firm resources away from hiring and investment and towards debt repayments, while allocating lenders resources away from new lending and towards the restructuring and resolution of the debt overhang.

1 Introduction

The unprecedented scale of credit and property market boom and busts around the 2007/08 financial crisis has given rise to a renewed interest in the role of leverage in the economic cycle. Research at the country level has shown that countries with the highest levels of pre-crisis credit growth experience the largest post-crisis collapses in output and investment.[1] Research on US households has shown that housing wealth shocks and household over-leverage have had severe impacts on consumption and employment growth (Mian et al., 2013; Dynan et al., 2012).

Separately to the literature on credit, property markets and the real economy, a well-established body of work has shown that excess leverage may negatively impact on firm performance and investment. Theoretically, this relationship has been grounded in an option-theoretic framework (Myers, 1977; Hennessy, 2004). An empirical literature on non-financial corporates has shown that debt overhang can negatively impact corporate investment (Aivazian et al., 2005; Cai and Zhang, 2011; Coricelli et al., 2012), while research on the Asian crisis has shown that excessive debt accumulation has an important role to play in explaining weak post-crisis investment growth (Coulibaly and Millar, 2011).

Using a unique loan-level dataset on the December 2013 credit exposures of Irish Small and Medium Enterprises (SMEs), we create a bridge between the two strands of literature outlined above. We construct measures of property-related indebtedness for firms whose core business activity is unrelated to the property market. In so doing we identify firms who borrowed at the same bank to avail of an environment of rising property values, who may now experience more difficulty in servicing their debts than would otherwise have been the case. This unveils a previously unidentified "enterprise investment channel" through which property market boom and bust cycles can impact post-crisis growth.

Expanding on the description of the data in McCann and McIndoe-Calder (2014), we quantify the extent of this property investment by non-property-related firms, and subsequently show that in all sectors of activity, firms with property-related debts have higher loan default rates than firms with

[1] For example, Task Force of the Monetary Policy Committee of the ESCB (2013) provide a summary of evidence from a range of previous financial crises. Data are also presented on pre-crisis debt accumulation and post-crisis investment levels. A clear negative relationship is exhibited, with Ireland being the euro area country with the largest debt accumulation to 2008 and largest subsequent investment collapse. Davis and Stone (2004) show that high debt-equity ratios at the aggregate level correlate with declines in investment after crises. Abiad et al. (2011) find that in the aftermath of credit booms and/or banking crises, "creditless recoveries", where output growth is lowered by one third and recovery is more protracted, are more than twice as likely than in other recoveries. Similarly, firms in industries with a high reliance on external finance suffer disproportionately during such recoveries. Claessens et al. (2009) find that "although recessions accompanied with severe credit crunches or house price busts last only three months longer, they typically result in output losses two to three times greater than recessions without such financial stresses".

debts only related to their core business, with the magnitude being close to double in some cases.[2] We formalise the analysis by entering indicators of both the *existence* and the *intensity* of SMEs' property exposures into a standard cross-sectional default model, showing that there is a role for both in explaining the higher default rates associated with property-related borrowings. These estimated effects are robust to the inclusion of a measure of total firm indebtedness, indicating that firm expansion into the property market has a detrimental impact beyond that of the firm's total debt level. Finally, a Propensity Score Matching (PSM, Leuven and Sianesi (2003)) estimator is used to attempt to control for the obvious selection issues surrounding the characteristics of those SME borrowers who entered the property market. The estimation reveals that roughly half of the 18 per cent differential in default rates between firms with and without property borrowings cannot be explained by the characteristics of firms selecting into property investment, i.e. the differential results from the impact of the property investments on the firm's debt service ability.

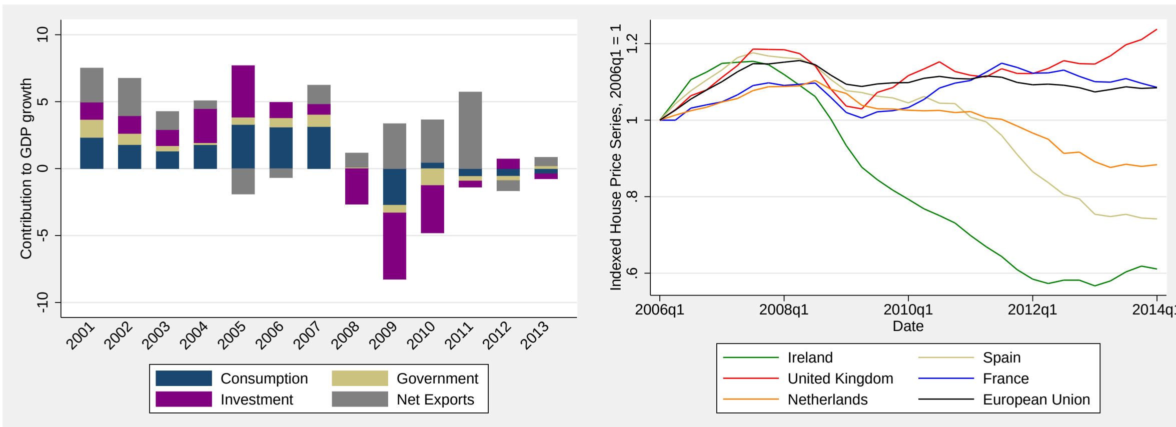
Ireland represents a uniquely suitable laboratory for the study of the interaction between the credit market, the property market and the real economy. Figure 1a plots the contribution to Irish GDP growth of consumption, government expenditure, investment and net exports between 2001 and 2013. The large role played by investment, of which between one third and one half related to construction in Ireland between 2003 and 2013, in the collapse in GDP growth in 2008, 2009 and 2010 is evident from the picture. Figure 1b places the decline in Irish house prices in a European context, showing that Irish house prices in 2012q2 were 49 per cent of their peak value in 2007q3, a collapse unparalleled in other European economies.

An existing body of literature has begun to deal with the loan arrears, consumption and investment effects of the Irish financial crisis. According to Central Bank of Ireland data, (Central Bank of Ireland, 2014b) there has been a huge increase in mortgage arrears greater than 90 days past due from 3 per cent in September 2009 to a peak of 12.9 per cent in September 2013. The knock-on effects of this mortgage arrears crisis on personal consumption have been examined by McCarthy and McQuinn (2014) and Lydon (2013). Meanwhile, the SME credit market has undergone an even steeper increase in loan default since the onset of the crisis, as evidenced by McIndoe-Calder (n.d.) and Central Bank of Ireland (2014a). The impact of this SME indebtedness on economic activity has been investigated

[2] "Default" is defined in this analysis following the Basel II guidelines, where either of the following two events has taken place: (i) the bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realising security (if held) (ii) the obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstanding.

Figure 1: Irish investment and house prices in boom and bust

(a) Components of GDP growth, 2001 to 2013 (b) House prices in selected countries, 2006 to 2014



Source: Central Statistics Office "Expenditure on GNP at Current Market Prices (Seasonally Adjusted) (Euro Million) by Expenditure Item and Quarter"; Eurostat house price series.

by Lawless et al. (2014), who show that Irish SMEs with higher debt-to-turnover ratios after the crisis are less likely to invest and to expand employment. Our work is related to all of the above papers in providing an insight into the spillover effect of investment in the overheated pre-2008 property market on firms' ability to repay their non-property-related, "core business" debts. To the best of our knowledge, ours is the first paper to identify this effect.

Our findings and methodology are also of relevance to the literature on enterprise credit risk. The literature on SME default modelling is relatively sparse when compared with the literature on larger corporate borrowers due to the difficulty in accessing data on borrowing SMEs, and generally relies on firms' financial ratios to predict default.[3] To the best of our knowledge, ours is the first study to include a measure of firms' property exposures in a model predicting firms' default. This can motivate researchers, particularly in countries which have experienced overheated property markets, to consider measures of firms' speculative exposure to debts not related to their core business activity for inclusion in default models.

Our findings have important policy implications, both in the context of the Irish economic recovery and more generally. Relevant to the Irish debate, the identification of the concentration of property

[3]Examples of such fundamentals-based SME credit risk research include McCann and McIndoe-Calder (2012) for Ireland, Behr et al. (2004) for Germany, Dyrberg-Rommer (2005) across France, Spain and the UK and Fidrmuc and Hainz (2010) for Slovakia. Papers such as Grunert et al. (2005) combine financial information with "soft information" on borrowers to improve the predictive accuracy of default models.

borrowings among a subset of large SME borrowers, echoing the finding of concentrated indebtedness in McCann (2014), can help to provide clarity on the extent of debt service difficulty in the enterprise population.

The extremely high default rate among these firms provides powerful motivation for a policy of speedy resolution and restructuring of the debts of this subset of Irish firms. The successful resolution of these cases has numerous aggregate implications for the Irish economy, given that the State is a shareholder in the banks holding these problematic loans, and that over two thirds of Irish private sector workers are employed by SMEs (Central Statistics Office, 2013; Lawless et al., forthcoming).

From the perspective of a general audience, the degree of loan default among SMEs having borrowed for property purposes should serve as a warning in economies experiencing rapid increases in property values. The diversion of enterprise credit away from potentially productive investments and towards the accumulation of an asset whose value is rising represents an additional channel through which boom-busts cycles in property markets can scar the productive capacity of the economy in the longer term.

The paper proceeds as follows: Section 2 describes the Central Bank of Ireland loan-level data used to identify SME-property linkages; Section 3 reports on the existence of property borrowings in the SME population; Section 4 reports results from formal empirical analysis of the role of property borrowings in loan default; Section 5 concludes.

2 Data: property exposures linked to SME debt

The Central Bank of Ireland collects loan-level data (LLD) bi-annually from the Irish domestic banks participating in the Financial Measures Programme.[4] The LLD spans mortgage, SME, corporate, commercial real-estate (CRE) and non-mortgage consumer finance loans. The data are submitted in June and December of each year since 2010. The data set used in this paper comes from the December 2013 wave of the LLD and provides information on a wide range of loan characteristics including outstanding balances, sector of activity and default status for the population of SME, CRE and mortgage loans outstanding. Whilst one third of the SME population carry little or no bank debt in Ireland (McCann, 2014), the LLD submitted to the Central Bank of Ireland accounts for over two-thirds of SME bank loans in Ireland.

The data are provided at loan level, with bank-specific identifier variables available that allow

[4] http://www.centralbank.ie/regulation/industry-sectors/credit-institutions/pages/financialmeasuresprogramme.aspx

firms and borrowers to be traced across asset classes within the same bank. Thus, firm identifiers ("Connection IDs") are used to link groups of loans and borrowers in the SME and CRE books of the same bank. It should be noted that the study is limited to exposures within the same bank; firms that borrow for property purchases with one bank and for core enterprise reasons with a different bank will not be captured in this dataset.

The SME loan book that comprises the core dataset of interest for this paper and to which the CRE and mortgage loan books are linked, is made up of 185,000 firms, 296,000 loans and €21 billion of outstanding balance. Figure A.1 shows the relative importance of each sector in the SME loan books and Central Bank of Ireland (2014a) provides additional descriptive statistics on this loan book.

3 Property exposures of SME loans

As described above, the firm and borrower-specific IDs in the LLD allow loans in differing asset classes and sectors of activity to be attributed to the same SME. These linked IDs allow property exposures to be associated to SMEs whose core business activity lies in a sector other than those related to real estate. Specifically, there are three ways in which property exposures can be attributed to an SME:

1. Exposures in the "Personal (Private Households)" sector relate to personal debts of SME owners. Firms may have loans classified in the sector relating to their own core business activity as well as this sector.
2. Firms' "Connection ID" can be located in both the SME and Commercial Real Estate asset classes.
3. An SME owner's personal property debts can be located in the mortgage book of the same bank.

Property exposures (1) and (2) are observable for all SME loans in the data set. Property exposure (3) is only available for a subset of the data in which the requisite identifiers for linking across data sets are contained. We begin with an examination of property exposures (1) and (2) for the complete sample, followed by an examination of the full range of property exposures (1) to (3) for the data subsample. A dummy variable *Property* is created which takes a one when an SME either falls into category (1) or (2) of the list above. It is possible that some property purchases falling into the Commercial Real Estate (CRE) asset class were in fact purchases of the operational premises of the business. The data set does not allow a distinction to be drawn between such a purchase and one for purely speculative purposes. However, given the investment climate in Ireland during the period in which most loans in the data set were originated, we feel that the existence of such purchases does not pose an important risk for the interpretation of the results of this study.

Table 1 shows that nearly all firms in the data, 95.55 per cent, are not exposed to property through the two channels identified in this section. When measured by the number of *loans* in the SME books, this number falls to 89.25 per cent, while when weighted by outstanding balance, 32 per cent of the SME loan book is at firms with a property exposure, indicating that larger borrowers are more likely to have non-core property-related borrowings.

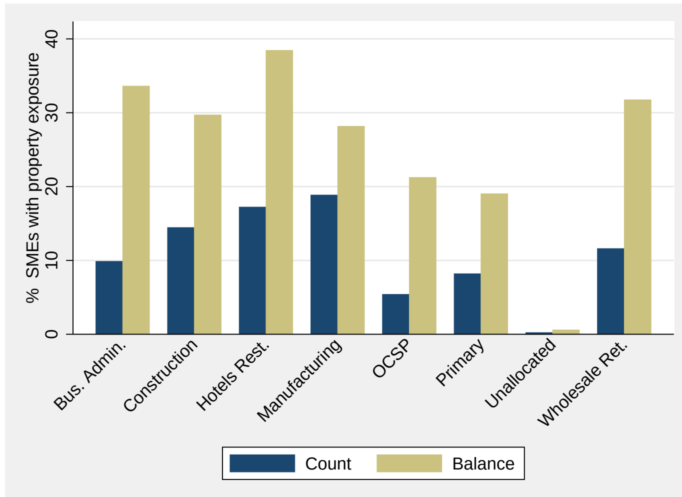
Table 1: Firms identified as having property exposure, full sample, December 2013

Measure	Sample	Property Exposure
Number of firms	184,758	4.45%
Number of loans	299,445	10.75%
Share of balance	€20.55bn	32.36%

Source: Central Bank of Ireland, Loan-Level Data, December 2013.
Note: Full sample, Personal (Private Households) and Commercial Real Estate exposures analysed. Mortgages omitted.

Figure 2 reports for each sector of activity, the percentage of SMEs that are exposed to property at the same bank using the definition employed in this section. As a point of reference, the relative importance of each sector in the SME credit market is reported in Figure A.1. In all sectors, the balance-weighted figure is higher than the percentage of loans, indicating that borrowers with larger SME exposures are more likely to have interlinked property exposures. The sectors where these linkages are most prevalent are the Business and Administrative Services, Hotels and Restaurants, and Wholesale and Retail sectors, where between 30 and 40 per cent of the SME balance outstanding is accounted for by enterprises that also have property exposures.

Figure 2: Percentage of SMEs with property exposures by sector, full sample



Source: Central Bank of Ireland, Statistics Data, December 2013.

3.1 Property investment and SME loan default

SMEs with property exposures are significantly more likely to default. By loan count, Table 2 reports that SMEs with property exposure have a default rate that is almost double that for those without CRE exposures (43 versus 23.4). When weighted by balance, the SME default rate for the 8,221 firms with a property exposure rises to 54.5 per cent.

Table 2: SME default rates for firms with and without property exposures, full sample

Property?	Count %	Balance %
No	23.4	33.6
Yes	43.0	54.5

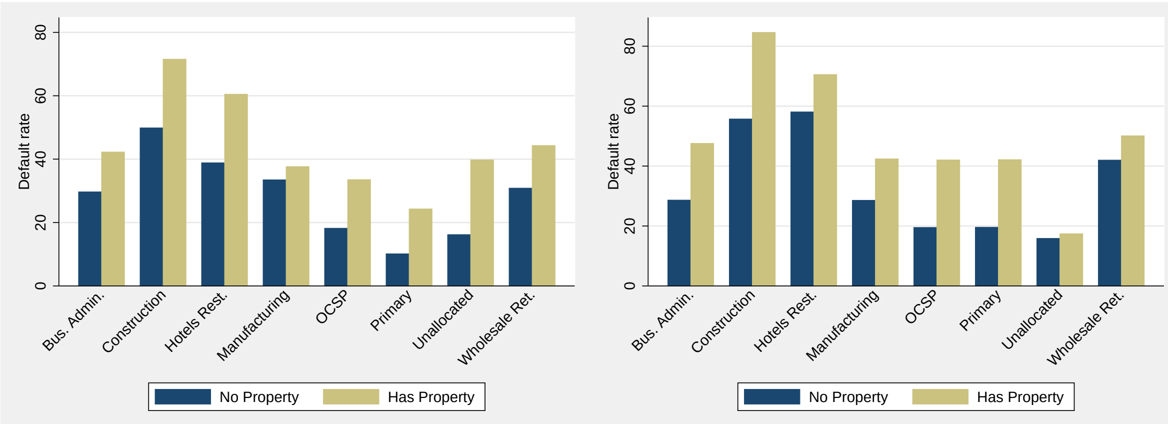
Source: Central Bank of Ireland, Loan-Level Data, December 2013.
Note: Full sample, Personal (Private Households) and Commercial Real Estate exposures analysed. Mortgages omitted.

Figure 3 reports sectoral default rates for loans with and without a property exposure. The default rate is highest in the Construction, and Hotels and Restaurants sectors. In all cases bar unallocated loans, the default rates in Figure 3b are higher than the corresponding rate in Figure 3a, indicating that higher-balance loans are more likely to be in default. A comparison of the blue and gold bars in every case in Figures 3a and 3b indicates that SMEs with property exposures have higher default rates than SMEs with loans only classified as relating to their core business.

Figure 3: Comparing default rates for SME firms with and without property exposure, full sample

(a) Default rate, number of loans

(b) Default rate, balance-weighted



Source: Central Bank of Ireland, Statistics Data, December 2013.

3.2 The intensity of property exposure

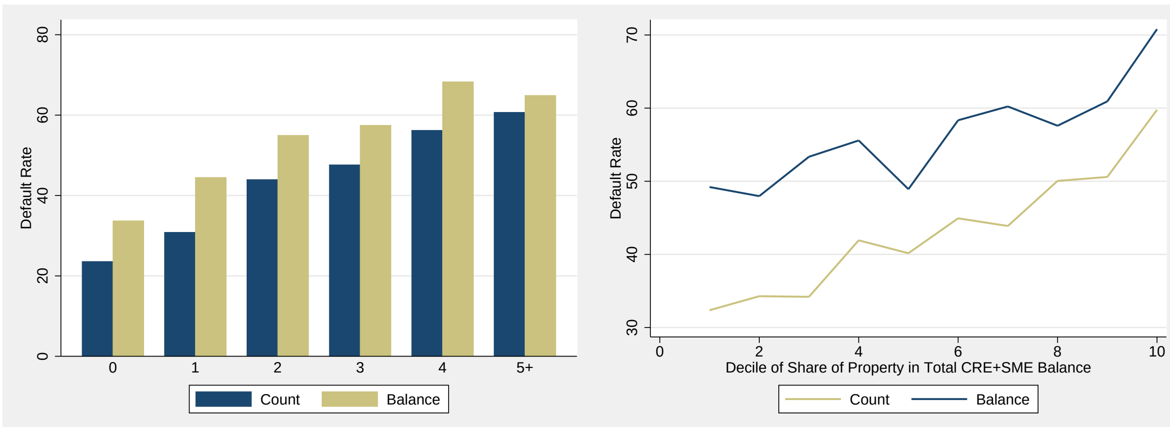
The analysis of the riskier profile of SME loans at firms with property exposures in Section 3 focussed solely on the *existence* of property exposures for SMEs. The relationship between property borrowing and loan performance is examined in more detail in this section by observing the *intensity* of firms' exposures to property, which is measured in three ways:

1. NP, the number of property loans attributable to the SME's connection ID at the same bank.
2. $OBPS$, the share of property exposures in the firm's total outstanding balance in the SME and CRE asset classes.
3. PSD, the share of the firm's total property-related debt that is in default.

Figure 4a confirms that the intensity of property exposure is related to loan default. As NP, the number of property-related loans held by the SME, increases, the default rate increases, with the only exception being the balance-weighted default rate for loans with five or more loans. There is considerable heterogeneity within the cohort of SMEs with property loans; SMEs with one property loan have a default rate of 30 per cent, while SMEs with five or more property loans have a default rate of 60 per cent. Uncovering this pattern suggests that important information will be missed by a model that focuses only on the *existence*, rather than the *intensity* of property borrowing.

Figure 4: Firm default rates by property intensity, full sample

(a) SME default rate by NP (b) SME default rate by decile of $OBPS$



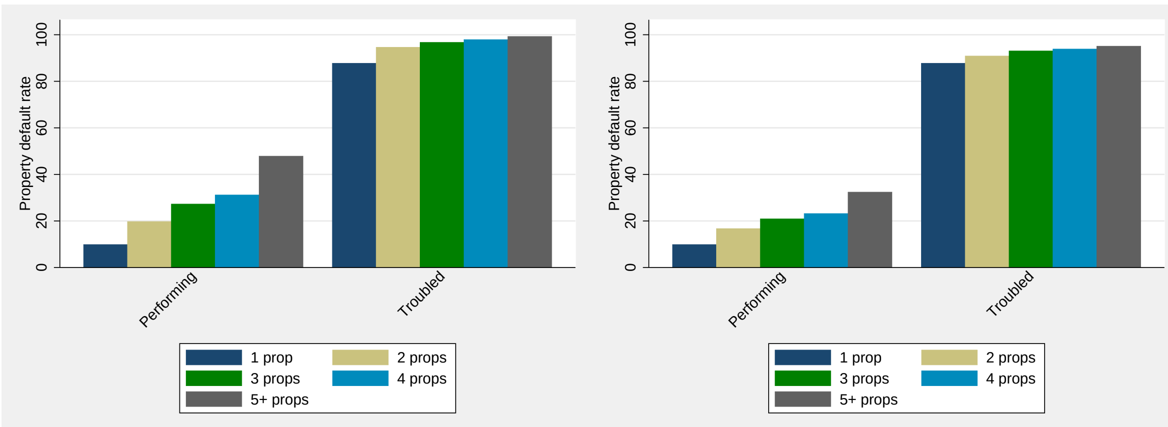
Source: Central Bank of Ireland, Statistics Data, December 2013.
Note: NP is the count of the number of property-related loans held by the firm. $OBPS$ is the percentage of the SME's total SME and CRE balance accounted for by property-related loans. Firms with zero property exposure omitted.

Figure 4b introduces our alternative proxy for property exposure intensity, $OBPS$, the share of the firm's total outstanding balance that is accounted for by property loans. The distribution of $OBPS$ for firms with property exposure is divided into deciles, with a clear positive relationship exhibited: the default rate in the 10th decile is close to double that in the first decile of $OBPS$. This confirms the relationship between property intensity and default presented in Figure 4a.

Figure 5 relates NP to the share of a firm's *property-related* debt that is in default. The analysis is split between firms with performing SME loans, and firms with at least one SME loan in default (labelled "Troubled"). The graph shows that default risk is highly correlated across "core" and property loans: where the SME is labelled "Troubled", the default rate on property-related debts is close to 100 per cent, irrespective of NP. Among SMEs with performing "core" debts, there is a positive relationship between NP and default on property debts: where a firm has more property-related loans, the default rate is likely to be higher.

Figure 5: Coincident firm and property credit risk, full sample

(a) Property default by property intensity, count (b) Property default by property intensity, balance



Source: Central Bank of Ireland, Statistics Data, December 2013.

3.3 Alternative measure of SME property exposure: data subsample

A subset of the loan-level data available to the Central Bank of Ireland allows us to track SMEs whose owners have a mortgage outstanding with the same bank, giving a third method of identifying firms' property exposures to complement those presented in Section 3. This data subset does not cover all lending to Irish SMEs, nor is it a representative sample of the Irish SME loan book.[5]

The overall SME default rate by count is 25.8 per cent in this dataset (see Table 3). Among SME loans with no identified linked mortgage, the rate is marginally higher at 26.2 per cent, and is substantially lower for SME loans with mortgage links, at 17 per cent. The default rate by balance is similar at 49 per cent for SMEs with and without mortgages, again suggesting that this type of property exposure is not necessarily more risky. This pattern is at odds with the data presented in Section 3, suggesting that owners' mortgages do not share the same characteristics as property loans housed in the Personal (Private Households) SME sector or the Commercial Real Estate asset class.

A more detailed look at the data can help explain the pattern uncovered in Table 3. When mortgaged SMEs are split between those with Principal Dwelling House (PDH) and Buy-to-Let (BTL) mortgages, it is revealed that the lower risk profile of owners' PDH mortgages explains the lower default rate among these firms. SMEs whose owners have BTL mortgages at the same bank share the characteristics of SMEs with property exposures outlined in Section 3, with balance-weighted default

[5] Figure A.2 shows the sectoral distribution of loans in this sub-sample. Appendix B provides further descriptive statistics on the property linking for this data subsample.

rates being one and a half times higher than those for SMEs without any linked mortgage. There is intuitive appeal to this finding, as BTL loans are more likely to be associated with speculative activity than mortgages for owner-occupation purposes. The existence of a relationship between SMEs linked to mortgage loans and SME default for *BTL loans only* suggests that it is appropriate to omit the PDH loans of SME owners when calculating total SME property exposure for this subsample of firms.

Table 3: Conditional SME default rates, sub-sample

Mortgage Link	PDH/BTL	SME default rate	
		Count	Balance
No mortgage	-	26.23	48.75
Mortgage	Either	17.03	49.53
Mortgage	PDH	14.78	39.91
Mortgage	BTL	26.60	69.51
Total		25.30	48.83
Total		25.76	49.31

Source: Central Bank of Ireland, Loan-Level Data, December 2013.

We combine data on property exposures from the mortgage book, the Personal (Private Households) SME sector and the Commercial Real Estate for the data subsample described in Table A.3. Table 4 provides the joint incidence of loan types by count and balance for the eight possible combinations of property exposure type. 23.6 per cent of SME loans are linked to property exposures, with this share rising to 43.2 per cent when weighted by outstanding SME balance, highlighting the pattern of larger borrowers having a higher propensity to borrow for property purchases. Of the 23.6 per cent of loans that have a property linkage, 19 per cent have linkages in just one of the three data sets at our disposal. In Columns (3) and (4) of Table 4, the mortgage exposures are restricted to BTL mortgages only. A comparison of columns (1) and (3) shows that of the 9 per cent of SMEs with a mortgage link, just under a fifth of these (1.52 per cent) relate to BTL borrowing. Overall, the impact of including only BTL exposures from the mortgage book is that the share of firms with property links falls from 23.6 to 14 per cent. However, the balance-weighted share only falls from 43 to 40 per cent, indicating that it is large SME borrowers who have predominantly borrowed for BTL rather than PDH purposes.

In Appendix B, the descriptive figures and tables of Sections 3, 3.1 and 3.2 are repeated for the subsample of loans described in this section. The figures show that the patterns of higher default among loans with property exposure, higher default where there is a higher number of property-related loans, and higher default where property loans are in default, also holds in this subsample of the data. Crucially, these patterns hold when BTL mortgages are considered alongside the property exposures identified in Section 3, but not when owner-occupied PDH mortgages are included. This data subsample will be used to show that the empirical results of the following sections are robust to an alternative definition of property exposure.

Table 4: Joint incidence of firms with SME, Mortgage, Personal and CRE exposure, subsample

	(1)	(2)	(3)	(4)
	All mortgages		Only BTL	
	Count	Balance	Count	Balance
No additional linked asset classes	76.42	56.79	83.97	59.45
Mortgage only	9.07	3.36	1.52	0.70
Personal only	4.57	9.95	4.85	10.29
CRE only	5.64	14.22	5.83	14.67
Mortgage and Personal	0.39	0.55	0.11	0.20
Mortgage and CRE	0.34	0.89	0.15	0.44
Personal and CRE	3.27	12.79	3.42	13.54
All	0.3	1.45	0.15	0.70

Source: Central Bank of Ireland, Loan-Level Data, December 2013.

4 Empirical analysis

The robustness of the clearly visible pattern of higher defaults for SMEs with property exposures is formalised in this section. In Section 4.1 the *Property* dummy variable, along with measures of the intensity and performance of property-related loans are entered into a standard baseline empirical model of SME loan default. In Section 4.2, the likely selection of riskier firms into property borrowing is treated using a Propensity Score Matching (PSM) estimator. This method constructs a counterfactual which allows us to provide an estimate of the difference in outcomes between a firm with property exposure and the same firm, *had the firm not borrowed to invest in property.*

4.1 Property exposures in a standard model of loan default

The relative impact of the *existence*, *intensity* and *performance* of property exposures on the probability of loan default (PD) can be ascertained by entering the measures defined in Sections 3.1 and 3.2 into a model of SME loan default. A baseline logistic regression model is run on the probability of loan default in December 2013. The covariates included in the baseline model are outlined in Table 5. The connection-level outstanding balance is entered in units of euros, which explains the small coefficient size. The coefficient sign, however, indicates that SME loans where the borrowing firm has a larger total exposure are more likely to default. Controlling for borrowing SMEs' overall indebtedness in this way is crucial for the interpretation of the property indicators that will enter the default model. The baseline model allows a flexible functional form for the impact of *loan* outstanding balance (OB) on the PD. Informed by Figure 6, it is clear that a standard quadratic or log-linear functional form will not accurately depict the relationship, given that default rates are very high in both the first and fifth quintile of the distribution, but relatively flat in the intermediate range of OB. For this reason, a flexible function form is allowed, whereby a distinct impact across and within quantiles of the OB distribution is modelled through the inclusion of three quantile dummies along with the interaction of OB with each quantile dummy. A standard quadratic functional form is chosen for loan age, allowing for the fact that loans are unlikely to default in the earliest stages of their existence, with PD rising as loans get older. However, it is generally acknowledged that there is a threshold loan age, beyond which loans remaining in existence are unlikely to default, due to a "survivor effect", leading to an expectation of a negative coefficient on the squared term.

A dummy for the existence of a positive undrawn balance is included, as positive undrawn facilities can be used as an indicator of positive sentiment of the loan officer towards the borrower. A dummy for amortising loans is also included, as descriptive statistics reveal that revolving facilities have a default rate roughly double that of amortising loans in the data set. Other standard predictors of loan default are included, such as dummy variables for the nine sectors categorised in Figure A.1, the three banks for whom SME loan data are available, and the eight NUTS3 regions of the Republic of Ireland.

Table 5: Covariates included in baseline logit default model

Covariate	Notes
Connection Balance	The total balance associated with a borrowing SME is controlled for, to distinguish the effect of property exposures from the effect of over-extended borrowers on PD.
Loan balance	A flexible function form is allowed by including balance, a dummy for three quantiles of the distribution, and the interaction between the level and the quantile of balance.
Undrawn facility dummy	A dummy that takes a one when a loan has a positive undrawn balance. In credit risk analysis this is often taken as an indicator of a favourable opinion of the lending officer compared to loans with no undrawn facility.
Loan Age	Loan age, in months, and its squared term enter the regression.
Sector dummy	Nine sectors as in Figure A.1.
Amortising dummy	Two categories: Amortising and Non-Amortising loans.
NUTS 3 regional dummy	BORDER, DUBLIN, MID-EAST, MID-WEST, MIDLAND, SOUTH-EAST, SOUTH-WEST, WEST.
Bank dummy	Three banks in the data set.

The results of the baseline logit PD model are reported in Table 6. The coefficients on the interaction terms between OB and the three terciles of its distribution show that, within each tercile, a larger OB leads to a higher PD. The coefficient on the second and third tercile indicate that the largest one third of loans have a higher PD than the smallest one third, while the intermediate one third of loans have a smaller PD than the smallest one third, in line with the pattern in Figure 6. The non-linear expected impact of loan age is confirmed with a positive sign on the level of loan age and a negative sign on the squared term. Figure 7 depicts the movement in $\hat{PD}$ for incremental increases in loan age and its squared term, with all other covariate impacts fixed at their mean. The pattern shown is one of an increasing PD up to 180 months, or a loan age of 15 years, after which the model predicts that PD falls as loans get older.

A number of sector dummies enter the model significantly, with the Construction sector being the only sector with a statistically significantly higher PD than the base category of Wholesale and Retail. A number of sectors are estimated to have lower PD than the base category: Business and Administrative Services, Other Community, Social and Personal Services (OCSP), Primary, and unallocated loans. In magnitude terms, the lowest PD, *ceteris paribus* is for the Primary sector, which consists mainly of agricultural loans. There is also statistically significant regional variation, with the Dublin, Mid-East and Midland NUTS 3 regions having a higher PD than the base category of the West region. In line with descriptive statistics on the data set, amortising loans have a 17.9 per cent lower probability of default than non-amortising loans. Finally, the inclusion of bank-specific effects is shown to be important, as both bank dummies enter significantly.

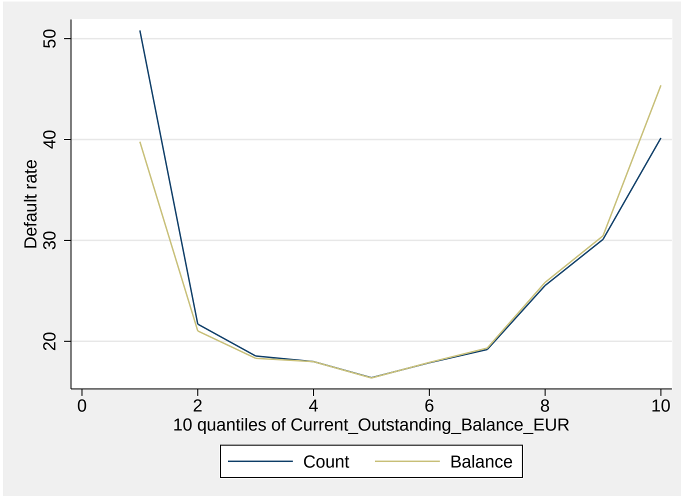
Measures of the existence, intensity and performance of property exposures are introduced into the baseline PD model in Table 7. In Column (1), the coefficient on the dummy variable *Property* indicates that, controlling for the range of covariates included in Table 6, SME loans with property exposures have a 5.27 per cent higher probability of default. The results of column (2) indicate that, controlling for the number of property-related loans held by the SME reduces the impact of the *existence* of property exposure to 3.5 per cent, while an additional property-related loan adds an additional 0.7 per cent to the loan's PD. In column (3), the variable NP is entered as a categorical, rather than cardinal variable. The base category in this regression is the zero-property category. The results suggest that having four and five-or-more property loans carries a statistically and economically significantly larger default risk (15.1 and 14.2 per cent larger than loans with no property exposure, respectively) than having one, two or three property loans (positive coefficients of 2.12, 8.2 and 7.3 per cent, respectively).

Table 6: Baseline logit default model

Connection Balance	1.04e-08***	Sector=Personal	-0.0119
	(4.56)		(-1.64)
Loan Balance	-0.00000405***	Sector=Primary	-0.144***
	(-3.99)		(-44.90)
Loan Balance Quartile 2	-0.0204***	Sector=Unallocated	-0.115***
	(-4.14)		(-40.73)
Loan Balance Quartile 3	0.00811**	nuts=BORDER	0.00874
	(2.37)		(1.56)
OB * Loan Balance Quartile 2	0.00000509***	nuts=DUBLIN	0.0111*
	(4.67)		(1.88)
OB * Loan Balance Quartile 3	0.00000403***	nuts=MID-EAST	0.0226***
	(3.98)		(3.49)
Positive Undrawn Balance	-0.296***	nuts=MID-WEST	0.00924*
	(-107.43)		(1.67)
Loan age	0.00423***	nuts=MIDLAND	0.0184**
	(60.14)		(2.56)
Loan age squared	-0.0000120***	nuts=SOUTH-EAST	0.00952
	(-46.61)		(1.57)
Sector=Business and Admin.	-0.0496***	nuts=SOUTH-WEST	-0.00624
	(-14.25)		(-1.22)
Sector=Construction	0.100***	Amortising	-0.166***
	(12.27)		(-48.19)
Sector=Hotels and Restaurants	-0.00538	Bank 1	0.111***
	(-0.97)		(9.18)
Sector=Manufacturing	-0.00738	Bank 2	0.197***
	(-1.11)		(13.94)
Sector=OCSP	-0.0167***		
	(-3.75)		
Pseudo R^2	0.280		
N	254,467		

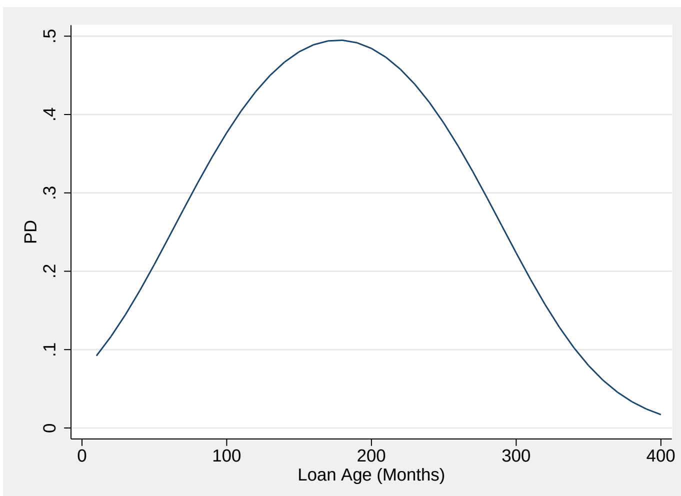
Marginal effects; t statistics in parentheses, Standard errors clustered at Connection level
* $p < .1$, ** $p < .05$, *** $p < .01$

Figure 6: SME default rates by decile of outstanding balance, December 2013



Source: Central Bank of Ireland, Statistics Data, December 2013.

Figure 7: Non-linear effect of loan age on PD, baseline model of Table 6



Source: Central Bank of Ireland, Statistics Data, December 2013.

Column (4) of Table 7 introduces the variable $OBPS$, which is the share of property exposure in the firm's total loan balance, measured between zero and one. This variable enters the equation significantly, with a 1 per cent increase in this share leading to a one-tenth of one per cent increase in PD. Controlling for both NP and $OBPS$ in column (5), the impact of a one per cent higher property share on PD falls from .1 of one per cent in column (4) to .09 of one per cent. Finally, the inclusion of a categorical variable in place of NP in column (6) reduces the magnitude of the effect of one percentage point in $OBPS$ on PD to .7 of one per cent.

Finally, Column (7) of Table 7 introduces SPD which measures the share of property exposure in default. The default correlation across asset classes is evident from the large statistically significant coefficient on SPD, indicating that a higher share of property loans in default is a strong predictor that a firm's SME loans are also likely to be in default.

Table 7: Logit default model with measures of property exposure, full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Property$	0.0527***	0.0351***		0.00297	-0.000750		-0.176***
	(6.05)	(3.37)		(0.27)	(-0.07)		(-36.40)
NP		0.00731*			0.00362		
		(1.73)			(0.86)		
1 property			0.0212**			-0.00747	
			(2.44)			(-0.70)	
2 properties			0.0821***			0.0352**	
			(5.50)			(2.03)	
3 properties			0.0730***			0.0232	
			(2.85)			(0.85)	
4 properties			0.152***			0.0876**	
			(4.23)			(2.40)	
5+ properties			0.142***			0.0654*	
			(4.11)			(1.91)	
$OBPS$				0.103***	0.0939***	0.0784***	
				(7.06)	(6.23)	(4.90)	
SPD							0.622***
							(33.22)
Pseudo R^2	0.281	0.282	0.282	0.282	0.282	0.283	0.330
N	254,467	254,467	254,467	254,467	254,467	254,467	254,467

Source: Central Bank of Ireland, Loan-Level Data, December 2013.
Note: Marginal effects; t statistics in parentheses; standard errors clustered at Connection level. * $p < .1$, ** $p < .05$, *** $p < .01$.
Note: Full range of covariates reported in Table 5 and 6 included in all specifications. $Property$ is a dummy variable indicating the existence of a property exposure; NP is a count of the number of property loans per SME; $OBPS$ is the share of property loans in the firm's total outstanding balance. The reference category for the variables "1 property" to "5+ properties" is the "Zero properties" category. SPD is the share of the firm's property-related debt that is in default, measured between 0 and 1. Loans with $NP > 22$ are excluded from all specifications, as these represent the 100th percentile of the non-zero property loan count distribution. These 417 loans represent 0.13 per cent of the total sample.

In Table 8, we examine the robustness of the results of Table 7 to the alternative definition of property exposures which includes an additional property type, BTL mortgages, as outlined in Section 3.3. Coefficient signs and statistical significance levels are extremely stable across the two samples and methods of measurement, however coefficient magnitudes are larger in the subsample where owners' Buy-to-Let mortgages are included in the measure of property exposure. The $OBPS$ variable does not enter the regression significantly when the number of properties, or a categorical variable in place of NP, is also included in the regression specification.

Table 8: Logit default model with measures of property exposure, subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Property	0.0996***	0.0738***		0.0775***	0.0660***		-0.148***
	(7.99)	(4.61)		(4.21)	(3.38)		(-16.86)
NP		0.0104			0.00982		
		(1.42)			(1.31)		
1 property			0.0556***			0.0584***	
			(4.82)			(3.28)	
2 properties			0.159***			0.163***	
			(7.00)			(5.33)	
3 properties			0.158***			0.163***	
			(4.07)			(3.49)	
4 properties			0.283***			0.289***	
			(4.91)			(4.49)	
5+ properties			0.238***			0.245***	
			(4.35)			(4.06)	
$OBPS$				0.0352*	0.0149	-0.00543	
				(1.86)	(0.79)	(-0.28)	
SPD							0.549***
							(22.54)
Pseudo R^2	0.380	0.380	0.382	0.380	0.380	0.382	0.422
N	139,979	139,979	139,979	139,979	139,979	139,979	139,979

Source: Central Bank of Ireland, Loan-Level Data, December 2013.
Note: Marginal effects; t statistics in parentheses; standard errors clustered at Connection level. * $p < .1$, ** $p < .05$, *** $p < .01$.
Note: Full range of covariates reported in Table 5 and 6 included in all specifications. *Property* is a dummy variable indicating the existence of a property exposure; NP is a count of the number of property loans per SME; $OBPS$ is the share of property loans in the firm's total outstanding balance. The reference category for the variables "1 property" to "5+ properties" is the "Zero properties" category. SPD is the share of the firm's property-related debt that is in default, measured between 0 and 1. Loans with $NP > 22$ are excluded from all specifications, as these represent the 100th percentile of the non-zero property loan count distribution. These 222 loans represent 0.16 per cent of the total sample.

4.2 Using Propensity Score Matching to estimate the effect of property on default

Estimates from Table 7 suggest that, controlling for a range of factors that one would expect to predict default, SMEs with property exposures have a 5.27 per cent higher default risk, with more than half of this explanatory power accounted for by measures of the *intensity* of property exposure. An alternative way in which one can identify the effect of property exposures on default risk is to more formally attempt to construct a counter-factual observation for each SME loan with a property exposure to identify the effect of property borrowing on default. One standard way in which such counter-factuals are constructed is Propensity Score Matching (PSM, Leuven and Sianesi (2003)). Loans with property exposures are referred to in the language of this methodology as those in the treatment group ($D = 1$), while those loans with no property exposure are referred to as the control group ($D = 0$). Our outcome variable, Y is loan default.

Given that the causal effect of a treatment for unit i, Y_{i1} - Y_{i0}, is unobservable, the researcher can estimate the average treatment effect on the treated, ATT

$$E(Y_1|D = 1) - E(Y_0|D = 1) \tag{1}$$

The counter-factual $E(Y_0|D = 1)$ is the outcome that those in the treatment group would have experienced, on average, had they not been subject to the treatment. PSM allows the researcher to construct the counter-factual on the assumption that all relevant differences between the treatment and control groups are captured by their observables X. A probit regression is run $p(x) = Pr(D = 1|X = x)$, with the predicted probability of $D = 1$ for all observations referred to as the propensity score. In the case of "nearest neighbour" matching, for unit i in the treatment group, the estimator associates an observation j from the control group such that

$$C^0(p_i) = j : |p_i - p_j| = min|p_i - p_k| \tag{2}$$

i.e., each individual in the treatment group is matched to the individual in the control group with the most similar propensity score. The stage 1 probit regression run here is of the form:

$$\begin{aligned} Pr(Property) = fn(&Sector, Segment, InterestRate, UDD, ln(OB), Secured, \\ &Regional, LA, LA^2) \end{aligned} \tag{3}$$

The results are reported in Table 9. The PSM model is run firstly for the full sample of loans. Pre-match statistics show that there is a 19 per cent higher unconditional probability of default for firms with property exposures relative to those that do not. The PSM model then matches each property-exposed loan to the loan without property exposure that has the closest propensity score as estimated by the probit model (3). The sample means post-matching are compared to give the ATT of property exposure on loan default. Results suggest a highly statistically significant ATT of 6.71 per cent, meaning that roughly two-thirds of the default differential associated with SMEs with property exposure can be explained by the characteristics of the borrowing firms. The second row of Table 9 repeats the model for the subsample of loans described in Section 3.3. The ATT is estimated to be very similar in this subsample, at 5.42 per cent, indicating that model estimates are robust to an alternative definition of property exposure which includes Buy to Let investment mortgages.

Table 9: Propensity Score Matching results

Specification	N	Difference-in-Means pre-matching	ATT post-matching
Full sample	248,058	.1918 (.0030)	.0671 (.0058)
Restricted sample with BTL exposures	135,829	.1494 (.0035)	.0542 (.0065)

Source: Central Bank of Ireland, Loan-Level Data, December 2013.
Note: $Y = Property$ is a dummy variable indicating the existence of a property exposure. the outcome variable is a dummy for SME loan default. Explanatory variables used in stage one to match treatment to control loans are Sector, Segment ,Interest Rate, undrawn balance dummy, ln(outstanding balance), Connection Balance, Amortising Flag, Secured Flag, NUTS 3 regional dummy, loan age, loan age squared. Nearest-neighbour matching estimator used.

Sample means and t-test statistics for all covariates used in the full sample PSM model are generated for the unmatched and matched samples in Tables A.1 and A.2, respectively. The difference in means between treated and untreated groups in the unmatched sample is almost always significant. However, matching observations based on all 28 covariates reduces the mean difference for all covariates, usually to a level not found to be significant at the 10 per cent level.

5 Conclusion

Empirical analyses at the country and household level show that high leverage can negatively affect growth, investment, consumption and employment growth. The literature on non-financial corporates finds that high levels of indebtedness can impede firms' ability to invest for productive means. This paper contributes to both the country-level credit, property-markets and real economy and the firm-level leverage literatures by explicitly identifying and examining the effects of property-related debt overhang on the performance of firms whose core business does not relate to the property sector.

We find that between 4.44 and 16.03 firms (32.25 - 40.55 per cent when balance-weighted) have property-related debts. These firms have substantially higher SME loan default rates than do firms with no such observed linkages. Further, the *firm* and *property* default rates increase with the intensity of property exposure. Using the existence, intensity and performance of property-related debt to augment a standard firm level probability of default model we find that all three measures of property-debt exposure strongly predict default in the large sample of SME loans for which we have information on in Ireland. These findings are robust to a wider definition of property exposure as well as an alternate default model specification. Finally, propensity score matching techniques, matching on 28 available covariates, show that the relationship between property borrowing and loan default is robust to choice of methodology. We find a highly statistically and economically significant 6.71 per cent effect of property exposures on the probability of SME loan default.

The policy implications of this analysis are stark; pre-crisis property-related borrowings have an economically and statistically large impact on the likelihood that firms will default on their "core" enterprise debts. The reallocation of productive capital towards investment in an over-valued asset is confirmed to have had long-lasting impacts on the financial health of Irish SMEs. Such a pattern suggests that policy makers must take account of this additional channel through which over-heating property markets can harm long-term economic growth prospects. In the context of the post-2008 Irish economic recovery, the decoupling of non-core property-related debt from the debts of an otherwise potentially viable SME represents an area of crucial policy importance. It is to be hoped that efforts currently underway to provide for such a resolution of the SME debt overhang will contribute positively to private sector investment and employment growth in the coming years.

References

Abiad, Abdul, Giovanni DellAriccia, and Bin Li, "Creditless Recoveries," CEPR Discussion Papers 8301, C.E.P.R. Discussion Papers March 2011.

Aivazian, Varouj A., Ying Ge, and Jiaping Qiu, "The impact of leverage on firm investment: Canadian evidence," *Journal of Corporate Finance*, March 2005, *11* (1-2), 277–291.

Behr, Patrick, André Güttler, and Dankwart Plattner, "Credit Scoring and Relationship Lending: The Case Of German SME," 2004.

Cai, Jie and Zhe Zhang, "Leverage change, debt overhang, and stock prices," *Journal of Corporate Finance*, June 2011, *17* (3), 391–402.

Central Bank of Ireland, SME Market Report 2014 H1, Central Bank of Ireland 2014.

_ , "Residential Mortgage Arrears and Repossessions Statistics," Statistical Release Q1 2014, Central Bank of Ireland 2014.

Central Statistics Office, "Business in Ireland 2011," Statistical Release, Central Statistics Office 2013.

Claessens, Stijn, M. Ayhan Kose, and Marco E. Terrones, "What happens during recessions, crunches and busts?," *Economic Policy*, October 2009, *24*, 653–700.

Coricelli, Fabrizio, Nigel Driffield, Sarmistha Pal, and Isabelle Roland, "When does leverage hurt productivity growth? A firm-level analysis," *Journal of International Money and Finance*, 2012, *31* (6), 1674–1694.

Coulibaly, Brahima and Jonathan Millar, "Investment Dynamics in the Aftermath of the Asian Financial Crisis: A Firm-Level Analysis," *International Finance*, 06 2011, *14* (2), 331–359.

Davis, E. Philip and Mark R. Stone, "Corporate financial structure and financial stability," *Journal of Financial Stability*, September 2004, *1* (1), 65–91.

Dynan, Karen, Atif Mian, and K.M. Pence, "Is a Household Debt Overhang Holding Back Consumption? [with Comments and Discussion]," *Brookings Papers on Economic Activity*, 2012, pp. pp. 299–362.

Dyrberg-Rommer, Anne, "A Comparative Analysis of the Determinants of Financial Distress in French, Italian and Spanish firms," Working Paper Series 26, Danmarks Nationalbank May 2005.

Fidrmuc, Jarko and Christa Hainz, "Default rates in the loan market for SMEs: Evidence from Slovakia," *Economic Systems*, June 2010, *34* (2), 133–147.

Grunert, Jens, Lars Norden, and Martin Weber, "The role of non-financial factors in internal credit ratings," *Journal of Banking & Finance*, 2005, *29* (2), 509 – 531.

Hennessy, Christopher A., "Tobin's Q, Debt Overhang, and Investment," *Journal of Finance*, 08 2004, *59* (4), 1717–1742.

Lawless, Martina, Brian O'Connell, and Conor O'Toole, "SME Recovery Following a Financial Crisis: Does Debt Overhang Matter?," Working Paper XXXX, Economic and Social Research Institute 2014.

_ , Fergal McCann, and Tara McIndoe Calder, "SMEs in Ireland: contributions, credit and economic crisis," *Policy Studies*, forthcoming, *0* (0), 1–23.

Leuven, Edwin and Barbara Sianesi, "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing," Statistical Software Components, Boston College Department of Economics April 2003.

Lydon, Reamonn, "Do households with debt problems spend less?," Economic Letters 02/EL/13, Central Bank of Ireland May 2013.

McCann, Fergal, "Profiling the indebtedness of Irish SMEs," Economic Letters 03/EL/14, Central Bank of Ireland May 2014.

_ and Tara McIndoe-Calder, "Determinants of SME Loan Default: The Importance of Borrower-Level Heterogeneity," Research Technical Papers 06/RT/12, Central Bank of Ireland September 2012.

_ and _ , "Irish SME Property Exposure: What do we Know?," Economic Letters 08/EL/14, Central Bank of Ireland August 2014.

McCarthy, Yvonne and Kieran McQuinn, "Deleveraging in a highly indebted property market: Who does it and are there implications for household consumption?," Research Technical Papers 05/RT/14, Central Bank of Ireland March 2014.

McIndoe-Calder, Tara, "The probability of default transitions for Irish SMEs," mimeo, Central Bank of Ireland.

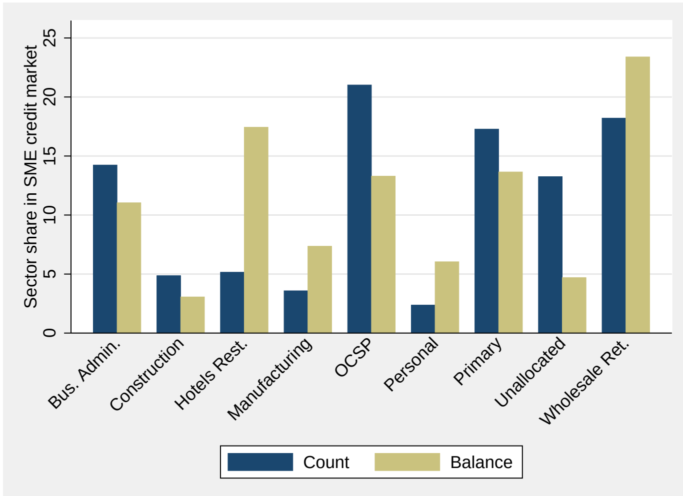
Mian, Atif, Kamalesh Rao, and Amir Sufi, "Household Balance Sheets, Consumption, and the Economic Slump," *The Quarterly Journal of Economics*, 2013, *128* (4), 1687–1726.

Myers, Stewart C., "Determinants of corporate borrowing," *Journal of Financial Economics*, 1977, *5* (2), 147–175.

Task Force of the Monetary Policy Committee of the ESCB, "Corporate finance and economic activity in the euro area," Occasional Paper Series 151, European Central Bank August 2013.

A Appendix

Figure A.1: Sectoral Distribution, full sample



Source: Central Bank of Ireland, Statistics Data, December 2013.

Table A.1: Sample means and t-test statistics, unmatched sample

	Mean		t-test		Mean		t-test
Variable	Treated	Control	t	Variable	Treated	Control	t
Sector==Business and Admin.	0.17	0.14	12.14	Not amortising	0.44	0.37	21.02
Sector==Construction	0.09	0.05	24.86	Secured ststus unknown	0.05	0.27	-76.03
Sector==Hotels and Restaurants	0.11	0.05	38.10	Secured	0.66	0.41	74.45
Sector==Manufacturing	0.08	0.03	36.30	Unsecured	0.29	0.32	-8.72
Sector==OCSP	0.14	0.23	-33.51	nuts==BORDER	0.09	0.10	-6.85
Sector==Primary	0.16	0.19	-9.71	nuts==DUBLIN	0.20	0.16	14.94
Sector==Unallocated	0.00	0.14	-58.81	nuts==MID-EAST	0.11	0.10	1.39
Sector==Wholesale and Retail	0.25	0.17	29.97	nuts==MID-WEST	0.12	0.14	-9.49
Micro-SME	0.06	0.77	-256.12	nuts==MIDLAND	0.05	0.07	-11.91
SME	0.94	0.23	256.12	nuts==SOUTH-EAST	0.11	0.12	-5.99
Interest rate	5.33	6.68	-84.20	nuts==SOUTH-WEST	0.23	0.19	16.79
Positive Undrawn Balance	0.36	0.43	-21.00	nuts==WEST	0.09	0.11	-7.48
Ln(outstanding balance)	10.20	8.70	89.27	Loan age	92.44	60.29	62.58
Amortising	0.56	0.63	-21.02	Loan age squared	15,609.00	9,103.20	35.82

Source: Central Bank of Ireland, Loan-Level Data, December 2013.

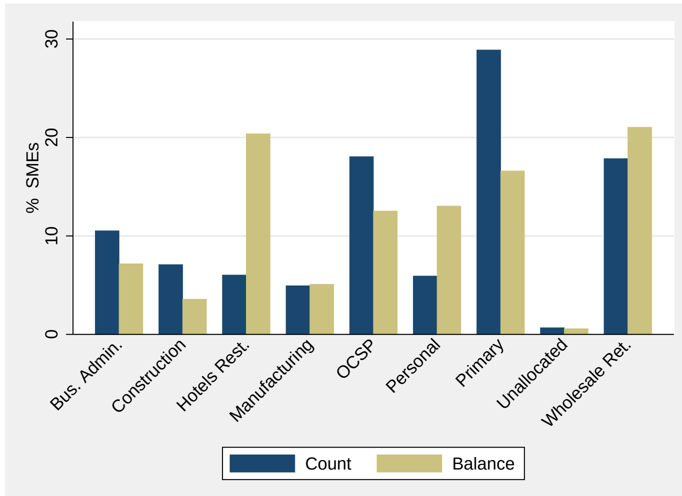
Table A.2: Sample means and t-test statistics, matched sample

	Mean		t-test		Mean		t-test
Variable	Treated	Control	t	Variable	Treated	Control	t
Sector==Business and Admin.	0.17	0.16	3.13	Not amortising	0.44	0.44	0.43
Sector==Construction	0.09	0.09	-3.32	Secured ststus unknown	0.05	0.04	5.18
Sector==Hotels and Restaurants	0.11	0.11	0.81	Secured	0.66	0.66	-0.22
Sector==Manufacturing	0.08	0.08	0.79	Unsecured	0.29	0.30	-2.05
Sector==OCSP	0.14	0.14	-0.63	nuts==BORDER	0.09	0.09	-1.12
Sector==Primary	0.16	0.18	-4.71	nuts==DUBLIN	0.20	0.19	3.28
Sector==Unallocated	0.00	0.00	1.01	nuts==MID-EAST	0.11	0.10	0.30
Sector==Wholesale and Retail	0.25	0.24	2.90	nuts==MID-WEST	0.12	0.12	-0.50
Micro-SME	0.06	0.06	-0.02	nuts==MIDLAND	0.05	0.05	-0.78
SME	0.94	0.94	0.02	nuts==SOUTH-EAST	0.11	0.11	0.76
Interest rate	5.33	5.34	-0.46	nuts==SOUTH-WEST	0.23	0.24	-1.73
Positive Undrawn Balance	0.36	0.36	0.43	nuts==WEST	0.09	0.09	-0.84
Ln(outstanding balance)	10.20	10.26	-2.57	Loan age	92.44	92.35	0.11
Amortising	0.56	0.56	-0.43	Loan age squared	15609.00	15651.00	-0.14

Source: Central Bank of Ireland, Loan-Level Data, December 2013.

B Tables and Figures on data sub-sample with BTL exposures

Figure A.2: Sectoral Distribution, subsample



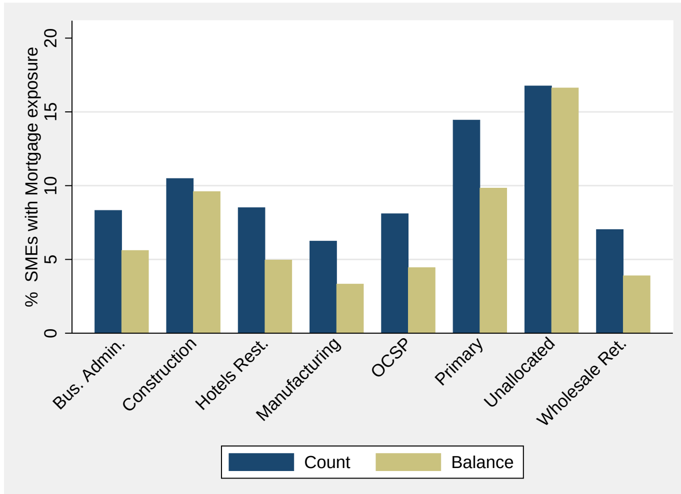
Source: Central Bank of Ireland, Statistics Data, December 2013.

Table A.3: Percentage of firms with SME and Property Exposures, sub-sample

	$N = 75,578$		$N = 140,534$		$N = €10.24bn$	
	No Property	Property	No Property	Property	No Property	Property
Micro	70.73	2.70	53.38	2.66	10.71	0.73
SME	19.91	6.65	29.01	14.95	48.74	39.82
Total	90.65	9.35	82.39	17.61	59.45	40.55

Source: Central Bank of Ireland, Loan-Level Data, December 2013.

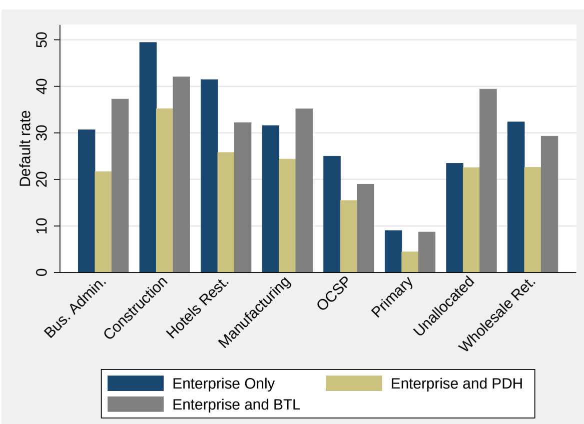
Figure A.3: Percentage of SMEs with Mortgages exposures, sub-sample



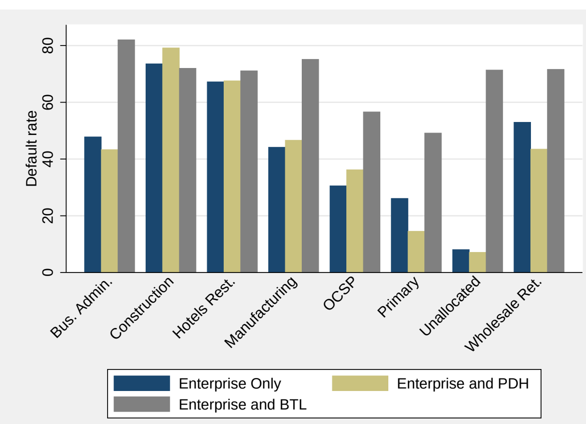
Source: Central Bank of Ireland, Statistics Data, December 2013.

Figure A.4: Comparing default rates for firms with and without Mortgage exposure, sub-sample

(a) Default rate, number of loans



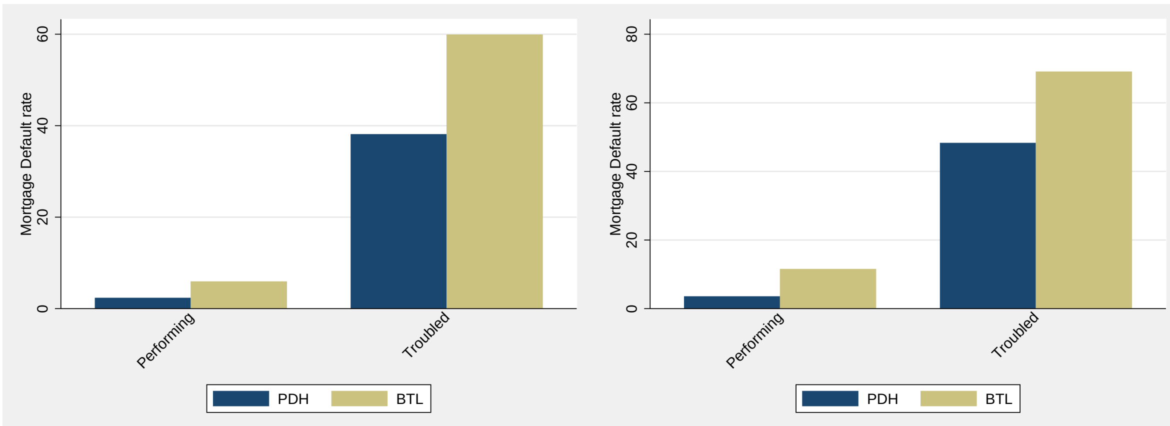
(b) Default rate, balance-weighted



Source: Central Bank of Ireland, Statistics Data, December 2013.

Figure A.5: Mortgage Default Rates for Firms with Mortgage exposures, sub-sample

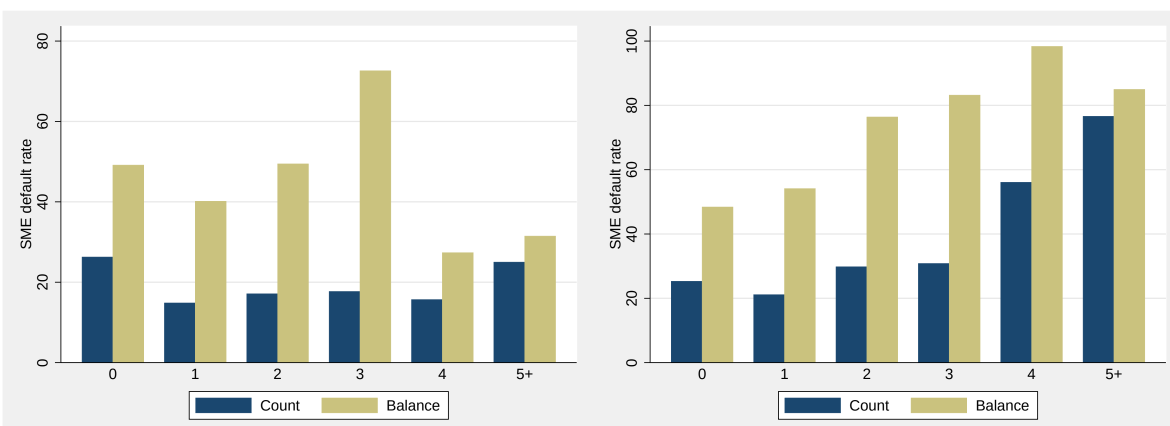
(a) Mortgage Default rate, number of loans (b) Mortgage Default rate, balance-weighted



Source: Central Bank of Ireland, Statistics Data, December 2013.

Figure A.6: Comparing default rates for firms by Mortgage exposure intensity, sub-sample

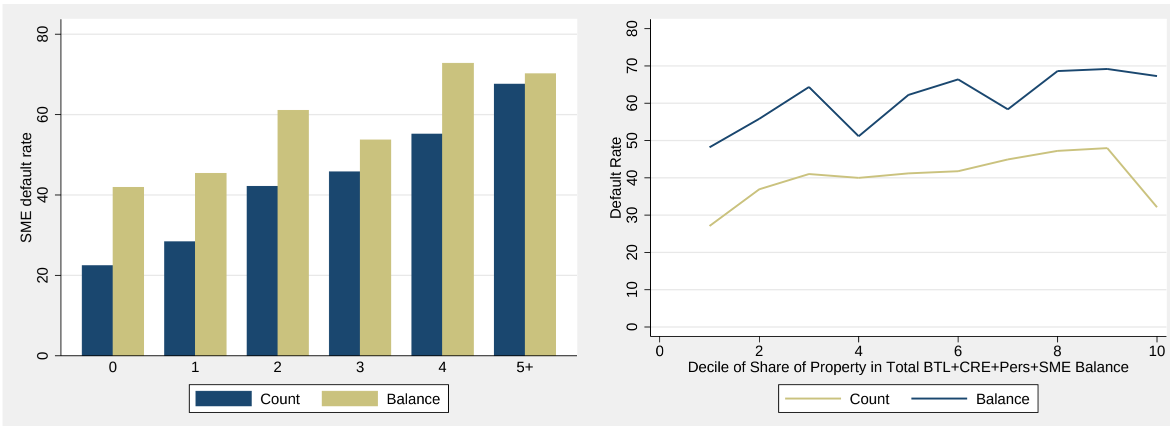
(a) SME Default rate, PDH links (b) SME Default rate, BTL links



Source: Central Bank of Ireland, Statistics Data, December 2013.

Figure A.7: SME default rates by property exposure intensity, subsample

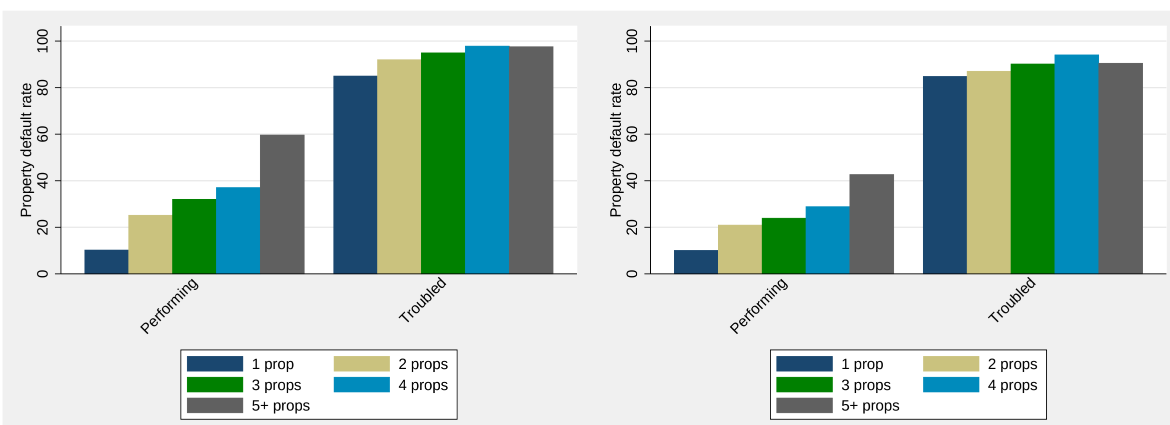
(a) Number of properties (b) Property share in total SME loan balance



Source: Central Bank of Ireland, Statistics Data, December 2013.

Figure A.8: Coincident firm and property credit risk, subsample

(a) Property default by property intensity, count (b) Property default by property intensity, balance



Source: Central Bank of Ireland, Statistics Data, December 2013.