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Late payments on mortgage loans and unemployment: Evidence from a German household panel

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Non-technical summary

Research Question

This paper presents an empirical analysis that supports the assessment in Deutsche Bundesbank (2024b), that the state of the labour market is an important factor for the likelihood of loan defaults in private residential property financing.

Contribution

The paper offers new insights into the factors driving mortgage loan defaults, particularly the risk of delayed mortgage payments following job loss. Moreover, the paper contributes new evidence on the interplay between a higher burden from debt service payments, unemployment and mortgage default.

Results

An important factor for the likelihood of loan defaults in private residential property financing is the state of the labour market. Our estimate shows that for each person who becomes unemployed, the probability of missing a mortgage payment increases by two percentage points. The longer someone remains unemployed, the greater the likelihood that they will fall behind on their mortgage payments. Additionally, the study shows that when a person's debt payments take up a large share of their net income, the likelihood of mortgage payment delays increases significantly if they lose their job.

Nichttechnische Zusammenfassung

Fragestellung

Dieses Papier präsentiert eine empirische Analyse, die die Einschätzung in Deutsche Bundesbank (2024b) unterstützt, dass der Zustand des Arbeitsmarktes ein wichtiger Faktor für die Wahrscheinlichkeit von Kreditausfällen bei der Finanzierung privater Wohnimmobilien ist.

Beitrag

Dieses Papier bietet neue Einblicke in die Faktoren, die zu Zahlungsausfällen bei Hypothekendarlehen führen, insbesondere das Risiko verspäteter Hypothekenzahlungen nach einem Arbeitsplatzverlust. Darüber hinaus liefert die Arbeit neue Erkenntnisse über das Zusammenspiel einer höheren Belastung durch Schuldendienstzahlungen, Arbeitslosigkeit und Hypothekenausfällen.

Ergebnisse

Ein entscheidender Faktor für die Wahrscheinlichkeit von Kreditausfällen bei privaten Wohnimmobilienfinanzierungen ist die Lage am Arbeitsmarkt. Unsere Schätzung zeigt, dass für jede Person, die arbeitslos wird, die Wahrscheinlichkeit, eine Hypothekenzahlung zu verpassen, um zwei Prozentpunkte steigt. Je länger jemand arbeitslos bleibt, desto größer ist die Wahrscheinlichkeit, dass er mit seinen Hypothekenzahlungen in Verzug gerät. Darüber hinaus zeigt die Studie, dass die Wahrscheinlichkeit von Hypothekenzahlungsverzögerungen signifikant steigt, wenn die Schuldendienstzahlungen einen großen Anteil am Nettoeinkommen einer Person ausmachen und diese ihren Arbeitsplatz verliert.

Late payments on mortgage loans and unemployment: Evidence from a German household panel *

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Abstract

This paper empirically analyses the effect of unemployment on mortgage loan late payments using German household panel data. Regressions with individual fixed effects suggest that for each person who becomes unemployed, the probability of missing a mortgage payment increases by two percentage points. The effect intensifies with the length of unemployment. When examining the interaction between mortgage late payments and households' debt service, we find that higher borrower-based risk amplifies the effect of unemployment. Crucially, the effect is non-linear. The odds of individuals who have lost their jobs making a late mortgage payment increases disproportionately for those with a debt service ratio of 30% to 40% of their income. This implies that capping debt service to income ratios can reduce the risk of mortgage defaults and buffer against labour market shocks, which is relevant for financial stability analysis and macroprudential regulation.

Keywords: Mortgage loans, default, unemployment, DSTI, macroprudential policy, financial stability

JEL classification: D14, G28, G21, G33, G51, J63, L85

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1 Introduction

Many studies show that household indebtedness (Schularick and Taylor, 2012; Mian and Sufi, 2018) and high household debt service (Drehmann and Juselius, 2014) are major sources of risk to financial stability. They are also robust predictors of crises. Unsurprisingly, high leverage also increases risks in the labour market (Kiley, 2022; Boyarchenko et al., 2023). Complementing the literature on the realisations of financial crises, the "at-risk"-literature shows that "leverage-like"-indicators are significant predictors of downside risks to the economy in general (Adrian, Boyarchenko, and Giannone, 2019). Lax lending standards significantly contribute to the build-up of household leverage or high household debt service. Macroprudential regulators have developed instruments which aim to prevent excessive household leverage and reduce the probability of financial crises. Borrower-based measures (BBMs) limit the risk of large collateral losses (LGD channel) or reduce the default risk of indebted households (PD channel).

Against this background, this paper examines financial stability risks associated with mortgage loans and high household debt. It empirically studies the link between unemployment and late mortgage payments using German panel data from 2006-2022. Furthermore, it examines the interaction between unemployment and debt service to income ratios (DSTI), providing insights into how high household debt amplifies the adverse impact of unemployment on mortgage loan risk.

The empirical results of this paper support the assessment in Deutsche Bundesbank (2024b) that the state of the labour market is an important factor for the likelihood of loan defaults in private residential property financing. The significance of the labour market lies in the impact of income shocks on driving the probability of default. Even if the collateral value (house value) drops significantly, lenders can avoid losses if households maintain a stable income and are able to continue making mortgage payments, regardless of their high debt levels. Unemployment disrupts the maintenance of a stable income. Further elaborating on the role of unemployment, our findings indicate that the duration of unemployment is a pivotal factor, as prolonged unemployment periods significantly increase the odds of mortgage payment difficulties.

Furthermore, our empirical findings underscore the critical role of high debt service burdens combined with the risk of unemployment in increasing mortgage loan risk. Specifically, the odds of late payments increase when a mortgage debtor with a higher DSTI ratio experiences a job loss. There is a non-linear effect of unemployment across the DSTI dimension, which we explain by a relationship between low income and high DSTI, which implies that lower-income mortgage debtors are particularly vulnerable to unemployment shocks. The vulnerability of low-income/high-debt mortgage holders is due to their limited financial buffers, which makes them more exposed to the income shock when faced with job loss.

The results are relevant for policy, as macroprudential regulators could potentially place caps on the high DSTI ratios at origination of the mortgage, thus reducing risks ex-ante. But they lack instruments to directly limit the risk of an increase in unemployment. These issues are also relevant from a more general regulatory perspective: if household default were driven by unemployment or other income and expenditure shocks but independent from household leverage or debt service, then a regulatory intervention with the aim of limiting DSTI would be hard to justify.

The rest of the paper is structured as follows. Section 2 explains the institutional context, providing background on the German labour market and unemployment insurance system. Section 3 introduces the data. Section 4 is the core of the paper and documents our main results on the effect of unemployment on late payments and the interaction with debt service, before we conclude in section 5.

2 Hypotheses and Institutional Setup

2.1 Simple model and hypotheses

Unemployment is an income shock as unemployment benefits replace only a portion of wages for individuals during unemployment. Over the course of unemployment, unemployment benefits typically decrease such that the long-term unemployed receive a lower income replacement than the short-term unemployed. Additionally, unemployment is associated with negative personal experiences, including social exclusions (Pohlan, 2019) and deteriorating health (Schmitz, 2011). These associations can reinforce the effect of income loss and reduce the resources for concerned persons to deal with negative financial consequences of unemployment. This applies all the more in the case of long-term unemployment.

In the following we formalise our argument and derive hypotheses. We focus on the case of no strategic default such that the probability of default (PD) is a function of the household's ability to pay, which depends on the budget constraint of the household. The household's ability to pay determines the PD, which depends on whether the household's income and liquid assets meet a critical expenditure threshold for debt service and other essential expenses like groceries or health. This is motivated by the evidence showing that low-income mortgage debtors have little financial headroom, as they allocate a large fraction of their income to servicing their mortgages and other essential expenses (Deutsche Bundesbank, 2022).

$$PD = \begin{cases} > 0, & \text{if Income + LiquidAssets} \leq \text{T(DebtService + Essential Expenses)} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

If an individual becomes unemployed, unemployment benefits replace the income, which are a fraction of the previous income determined by the replacement rate *r(c,t)*. This rate is always below 1 (*r(c,t)*< 1) and is a function of the unemployment duration t and other factors c such as country-specific generosity of unemployment benefits or person-specific attributes such as number of children, with the condition that *r(c,t+1)* $\leq$ *r(c,t)* to reflect the decrease in benefits over time. Additionally, liquid assets are subject to depletion during the period of unemployment, which we model by the decay rate *d(t)*$\leq$1 with *d(t+1)* $\leq$ *d(t)* which indicates that liquid assets can serve as a buffer against income loss for some time.

$$PD_t^{UE} = \begin{cases} > 0, & \text{if } r(c,t) \times \text{Income} + d(t) \times \text{LiquidAssets} \leq \text{T(DebtService + Essential Expenses)} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

From this we can derive the following directional hypotheses.

- Becoming unemployed increases the probability of default, as the replacement rate *r(c,t)* of income in case of unemployed is less than 1.
- The length of unemployment increases the probability of default, as the replacement rate *r(c,t)* and liquid assets decrease with unemployment length
- High debt service amplifies the probability of default when becoming unemployed or being unemployed for an extended period, as it represents a larger fixed expense that is harder to cover with reduced income. This amplification is non-linear. Unemployment becomes critical only when expenses relative to income and liquid assets exceed a certain threshold.

2.2 Institutional context

2.2.1 Mortgage loan market

The magnitude of the effect of unemployment depends on the institutional context. In a full recourse system, lenders have the legal right to repossess not only the property but also additional assets of the borrower if they default. This mechanism discourages strategic default, as borrowers face severe financial consequences beyond losing their home. Conversely, in non-recourse loan systems, lenders can only claim the property itself, which may lead to higher instances of strategic default. Additionally, the type of recourse influences how households respond to income shocks. Under full recourse, the severe repercussions of defaulting on a mortgage due to an income shock are more pronounced. Consequently, households have a strong incentive to prioritise their loan payments over other expenses to avoid avoid mortgage default.

In the United States, non-recourse mortgage loans increase the prevalence of mortgage defaults (Ghent and Kudlyak, 2011; Gete and Zecchetto, 2024). Both income shocks and strategic default are relevant factors (Ganong and Noel, 2023; Gerardi et al., 2018; Rendon and Bazer, 2021). In addition, unexpected expenditure and liquidity shocks can also drive household default (Anderson and Dokko, 2016; Gallagher, Gopalan, and Grinstein-Weiss, 2019; Low, 2023; Ganong and Noel, 2020).

For Europe, including Germany, full recourse is the typical setting. This discourages default and implies a prioritisation of debt service because of the more severe consequences of default. Nonetheless, there is significant variation among European countries with respect to the rights of borrowers. The OECD Foreclosure Regulation Index (van Hoenselaar et al., 2021) highlights this, in which Germany occupies a median position in comparison to other European countries. Countries such as Italy, the UK, and Ireland have more borrower-friendly policies, while policies in Austria and the Netherlands are stricter. Empirical evidence across European countries points towards unemployment as a trigger of mortgage repayment difficulties (Kelly and McCann, 2016; O'Toole and Slaymaker, 2021; Gerlach-Kristen and Lyons, 2018; Gaudêncio, Mazany, and Schwarz, 2019; Duygan-Bump and Grant, 2009). With respect to evidence for Germany, Korczak (2022) reports that unemployment is one of the most commonly cited reasons for over-indebtedness in data from surveys among over-indebted persons. Barasinska et al. (2023) shows a link between foreclosure and unemployment in regional data and over time: In federal states with high unemployment, there are more foreclosures.

2.2.2 Labour market and unemployment support

The unemployment benefit system is a relevant institutional factor. Hsu, Matsa, and Melzer (2018) document that within the United States, the effect of unemployment on mortgage delinquencies is mitigated by the generosity of the unemployment insurance scheme. OECD (2024) data on unemployment benefits rank the German scheme slightly above the OECD average for replacement in the first year and below the OECD average in subsequent years compared to other OECD countries. However, the replacement pay is much higher than in the United States, the UK and Ireland. The generosity of unemployment insurance in Germany relative to these countries implies that we expect a lower effect of unemployment than in previous studies.

Germany's two-tier unemployment benefits include a compulsory governmental insurance with 60-67% income replacement for up to a year, independent of the wealth and income of other household members. The second tier is the *Arbeitslosengeld 2 (ALG2)*, which covers only basic needs and is not dependent on previous income. To be eligible, the household in which the person resides must have low income and limited wealth.

To understand the context and data of our analysis we point out key labour market developments. Germany's labour market reforms (2003-2005) reduced unemployment benefits and increased market flexibility, which helped lower the unemployment rate (Dlugosz, Stephan, and Wilke, 2009; Kuhn, Hartung, and Jung, 2018; Launov and Wälde, 2016; Merkl and Sauerbier, 2024). During the 2020s, unemployment rates in Germany are at their lowest level since the German reunification in 1990.

Another key development is that during the COVID-19 pandemic, Germany expanded its *Kurzarbeit* (short-time work allowance) scheme to mitigate the economic impact on businesses and workers. The scheme allows companies facing economic difficulties to reduce employees' working hours instead of laying them off. The government compensates for a significant portion of the lost wages, thereby helping to preserve jobs and maintain income levels. As the scheme was generous, it was the first choice of firms hit by the pandemic and effectively cushioned employees against both becoming unemployed and significant income loss (Christl et al., 2023). Hence, the unemployment rate in Germany increased only slightly during the pandemic, contrary to the United States, which experienced a significant temporary spike in unemployment rates in 2020-21.

2.2.3 Real estate market and homeownership

Our sample covers the period from 2006 to 2022, during which residential real estate prices increased by an average of 4% year-over-year. Prices were mostly stagnant from 2006 to 2010, then increased by 6% year-over-year after 2010. At the same time, foreclosures of residential real estate have decreased around 8% year-over-year.

Germany has a low homeownership rate due to an extensive social housing sector, high transfer taxes and no mortgage interest tax deductions (Kaas et al., 2021). Mortgage debtors owning a home are wealthier, with a median net wealth of €326,000 compared to €16,000 Euro among tenants (Deutsche Bundesbank, 2023). They also have a higher level of income: the median annual net income of owners with a mortgage was €35,000 versus €25,400 for tenants (Deutsche Bundesbank, 2023). The majority of homeowners holds also comfortable levels of liquid assets, with the median owner having liquid assets amounting to 34% of their debt (Deutsche Bundesbank, 2024a).

Most mortgage loans have fixed interest rates and long maturities. This makes the debt service of individual borrowers insensitive to interest rate changes in the short term. The macroprudential toolkit currently includes an LTV ratio and an amortisation requirement. The German Federal Government has announced plans to create the legal basis for the two missing instruments (DSTI and DTI). However, Germany has not yet activated any BBMs.

2.2.4 Overall effect of institutional factors

Institutional features in Germany point to a lower effect of unemployment on mortgage loan risk compared to the United States. Factors that likely contain the effect are full recourse loans, relatively generous unemployment benefits, long-term fixed rate loans and the fact that homeowners hold relatively comfortable levels of liquid assets.

3 Data

3.1 Data set and sample

We use the Panel Study Labour Market and Social Security (Panel Arbeitsmarkt und Soziale Sicherung, PASS). It is a large-sample household survey of the German residential population, conducted annually. We provide a descriptive overview of the data and the number of observations in Table 1. As described by Trappmann et al. (2019), PASS oversamples unemployed persons and is therefore particularly useful when studying the consequences of unemployment.[1] We use all 16 waves collected between 2006 and 2023.

Within the data set, 15% of persons live in a homeowner household with an outstanding mortgage loan. This gives us around 30,000 person-wave observations. For comparison, 16% of persons are mortgage-free homeowners, 65% are tenants and 4% do not own and do not have to pay rent. As the focus of the survey is on unemployed persons, the data undersamples the German ownership rate (45% of German households are homeowners and 18% of households have a mortgage loan according to Deutsche Bundesbank (2023)). Figure 1 displays the share of persons in households with mortgage loans by person age. The prevalence increases with age, peaks at 45, and then falls. This is consistent with the fact that people buy homes with loans over the course of their lives and then pay the loan off over time, eventually in full. Young people are an exception, because they often live in a household with their parents.

3.2 Dependent variable: late payments on mortgage loans

The dependent variable is the incidence of late mortgage loan payments due to low ability to pay. To this end, we use the answer to the following question in the household questionnaire: “Does your household pay the rent for the apartment and / or the interest on the house one lives in always on time.”[2] The question is posed to both homeowners and tenants. However, our analysis is confined to homeowners who are currently servicing a mortgage. In addition, a sub-question takes into account the reason for the late payment: “And why do you not do this, for financial or other reasons?”[3] The use of responses citing “For financial reasons” ensures that only those foregone expenses that result from lack of financial means are taken into consideration and those that result from individual pref-

[1] The data set is provided by the German Federal Employment Agency and is available to researchers on request. We have access to this data with a user contract for the research project “Impact of labour market shocks on the servicing of residential real estate loans and material and social participation”.

[2] Notably, the question is asked in the present tense and does not refer to a specific time period. This is different to parallel questions in other household surveys; for instance, the German version of the Eurosystem’s Household Finance and Consumption Survey (HFSC) asks about payment difficulties within the last 12 months.

[3] The question is asked in the context of several questions on material deprivation, the households are asked whether they were able to pay for specific items or services and, if not, whether this was for financial reasons. The questions are used to construct an index of material deprivation.

erences are excluded. In line with this, we codify the dependent variable *Late Paym* as 1 if the responses are “We do not” and “For financial reasons” and 0 otherwise.

Figure 2 displays the share of our dependent variable by interview year. For comparative purposes, we also present the share of late payments attributed to ”For other reasons” and the combined share, which are included in our robustness checks. Additionally, we compare these figures with new mortgage net write-downs by German banks for mortgages issued to non-self-employed private households.[4] The year-on-year changes in late payments for financial reasons and banks’ write-downs generally move in parallel. Both shares decline over time, consistent with a booming residential real estate market in Germany. This parallel trend is particularly evident until 2020, after which the correlation appears to weaken.

The advantage of the late payment variable is that it provides us with a timely measure and sufficient variation in the dependent variable, even in non-crisis years. More stringent measures, such as home foreclosures or loan defaults, would yield a lower number of cases in household surveys. Moreover, such measures would introduce complications due to extended duration that elapses from the initial repayment difficulty until an eventual loan default.

3.3 Explanatory variable: Unemployment

We observe personal employment histories and also know the type of unemployment benefits – first tier or second tier (*ALG2*). We perform a number of robustness checks based on different definitions and types of unemployment.

We use the main employment status of the interviewed person as the baseline. We set a dummy variable *Unemployed* to 1 if a person is unemployed and to 0 if it is employed or has an other main status, e.g. student, housewife or pensioner. As the latter are not included in the labour force, we define the supplementary variable *Other Status* to directly capture the labour market status of those persons. We set the variable to 1 if the person is out of the labour force (i.e. it has an other main status), e.g. student, housewife or pensioner and to 0 if it is unemployed or employed (i.e. it is in the labour force). As an alternative, we repeat the previous analysis but set the unemployment dummy to one if at least one person in the household is unemployed. We also define an additional dummy variable *ALG2* to capture whether the household receives the second tier governmental benefits. As this benefit is received at the household level, we use this variable in the household setting (see also the subsection on institutional setup). We also use information

[4] The data are sourced from the Quarterly Borrower Statistics, which detail the credit exposure of German banks, categorised by borrower type and loan type. These statistics also encompass the valuation changes of these positions, specifically net write-downs (for further details, see Memmel, Gündüz, and Raupach, 2015). We calculate the ratio of annual net write-downs of mortgage loans to private households against the total outstanding loans by aggregating data from all banks. We use a lead variable to account for the time lag between late payments and bank write-downs. Note that this does not measure the probability of default, but rather realised losses, which result from default and loss given default. Data on banks’ PD estimates are not available for the full sample period.

on the length of unemployment, as we observe for each unemployed person-year the starting date of unemployment which we can compare to the interview date.

The share of unemployed persons (among homeowners with an outstanding mortgage) decreases over time (Figure 3), which is in line with the general development of the unemployment rate in Germany. Due to the oversampling of unemployed persons, the share of unemployed persons in the full survey is 2-3 times higher than the official unemployment rate; this is consistent with other sources. At the same time, the share of unemployed persons among homeowners with an outstanding mortgage is much smaller than the unemployment rate of tenants. With both effects together, the share of unemployed persons among homeowners with an outstanding mortgage in our data is similar to the official unemployment rate. The graph also displays the share of unemployed persons combined with the share of persons receiving a short-time work allowance, the temporary wage subsidy during the COVID-19 pandemic for employees with reduced working hours. We use the combined measure of unemployment and short-time work allowance in robustness checks.

Figure 4 displays the employment status in the following years conditional on being presently employed or unemployed. Employed persons mostly stay employed. The share of persons that are employed and then become unemployed is 1.8% in the next year. This figure then slightly increases to 2.0% in the second year before decreasing. The transition to another status is larger and increases by year. Unemployed persons mostly stay unemployed in the first year but the share decreases over time, converging to around 20%. Similarly, the share of persons becoming employed increases from around 20% to 40%.

4 Unemployment and late payments

4.1 Unemployment and late payments

Across all waves, unemployed persons consistently have a higher incidence of late payments compared to employed persons or persons with another status (Figure 5). The average difference of 3.3 percentage points suggests a strong correlation between unemployment and increased mortgage repayment difficulties.

Unemployment is endogenous because job loss depends on unobserved personal characteristics, which can affect late loan payments. To address this endogeneity, we employ individual fixed effects. This controls for unobserved, time-invariant characteristics of individuals that might influence both their likelihood of becoming unemployed and their ability to pay their mortgage. Although unemployment can result from heterogeneous causes (e.g., mass layoffs and individual decisions to resign), we focus on the overall impact of job loss on late payments, regardless of the reason.[5]

[5]Unlike the German Socio-Economic Panel, the PASS data does not include information on the reasons

Our regressions are at person-wave level with wave-and person fixed effects and standard errors clustered at person-level. Control variables are gender, age, years of education, number of children, marital status, unmarried partner living in the same household and number of persons in the household. Table 2 displays descriptive statistics. Table 3 displays the mean separately for persons who report late payments and persons who do not.

We obtain a significant effect of unemployment on late payments (Table 4, column 2). The model suggests that becoming unemployed increases the likelihood of late payments by 1.9 percentage point. This implies that becoming unemployed increases the odds of late payments from around 1% (the approximate mean) to around 3%. These numbers are lower compared to Gerardi et al. (2018), who report that unemployed are approximately 5 percentage points more likely to default than employed persons. This is expected because the institutional context in the United States makes a higher effect likely. The US data also show a higher average share of late payments: 3% compared approximately 1% in our data.

It is plausible that unemployment leads to late payments in the years following entry into unemployment because financial pressures intensify with prolonged unemployment. Plotting late payments against unemployment length suggests that late payments increase with unemployment duration (Figure 6). By contrast, for employed persons, late payments decrease with the duration of employment. To explore this, we estimate a model that substitutes the unemployment dummy with the number of unemployment months. Table 4 column 4 shows a significant positive effect of unemployment months which points to an effect of staying unemployed on late payments. An additional month of unemployment increases the odds of late payment by 0.1 percentage point. The inclusion of squared unemployment months as an additional variable yields a significant negative coefficient which indicates a concave relationship where the impact of additional unemployment duration diminishes with longer duration periods.

We also estimate a model using event time dummies for each year of unemployment. Table 4 column 5 shows a positive effect for all unemployment year dummies which is significant for the third year and longer than four years. However, the significance levels should be interpreted with caution due to reduced sample size for these event years. In summary, our event dummy estimate suggests that the risk of late payment increases with the length of unemployment.

Our finding that late payments increase with unemployment duration has important implications. First, it suggests that a longer-term reduction of income, rather than a short-term income shock, makes it difficult to repay mortgages. During the first years of unemployment, individuals can cope with the income reduction either by scaling back con-

for job loss, preventing us from distinguishing between mass layoffs and individual resignations. If unemployment after voluntary resignations is less likely to be linked to late payments than after mass layoffs, our combined measure of unemployment would likely underestimate its effect, as employees would only resign if confident they could still pay their mortgages.

sumption or using financial assets, but this ability diminishes over time. It could also mean that negative effects of unemployment such as social exclusion and deteriorating health develop over longer unemployment periods. This argues against strategic default, as it is unlikely that individuals would choose to live under financial constraints for several years before defaulting rather than defaulting immediately.

We also find a significant effect of unemployment when defining unemployment at the household-level (Table 5, column 2). The model predicts that becoming unemployed increases late payments by 0.9 percentage points, which is lower than the baseline estimate. In addition, we find a significant effect and quite strong effect for *ALG2*, i.e. for persons living in a household that receives second tier benefits of *Arbeitslosengeld 2*. The model predicts that receiving *Arbeitslosengeld 2* increases the odds of late payments by two percentage points. This confirms the previous finding of an effect of staying longer in unemployment. We also find a significant effect of total unemployment months of persons in the household (Table 4, column 4).

For robustness, we repeat the estimations with the alternative measure of late payments that includes all reasons, financial reasons and other reasons. Results are largely unchanged. We also repeat the estimations with an alternative measure of unemployment including the short-time work allowance introduced during the COVID-19 pandemic. The estimate is significant and indicates that unemployment or short-time work increases late payment by 1.6 percentage point, slightly lower than for unemployment alone.

4.2 Accounting for risk of the mortgage: DSTI

We evaluate the effect of the risk of a mortgage loan, quantified by the debt service to income ratio (DSTI). Previous research has shown that a higher debt service burden significantly increases the default risk of borrowers across various countries (Kelly, O'Malley, and O'Toole (2015) for Ireland, Holló and Papp (2007) for Hungary, Nier et al. (2019) for Romania, Dey, Djoudad, and Terajima (2008) for Canada, Fuster and Willen (2017) for the US). Some papers (e.g. Galán and Lamas (2019) for Spain) also consider interactions with other risk metrics like loan to value ratios and show that the risk metrics typically reinforce each other. Debt service ratios above 40%-50% are often identified as thresholds beyond which default risk increases disproportionately. However, definitions of income, debt service and measurement points vary widely, making exact comparisons difficult. Identifying non-linear effects is relevant for policy, as it could inform DSTI-cap regulations.

We compute DSTI using household debt service expenses and net income, truncating the ratio at the 1% and 99% percentiles to mitigate outliers. Figure 7 shows the DSTI distribution, with a median of 18% for new homeowners and 19% for existing homeowners.[6] In line with previous literature, high debt service is associated with an increase in

[6]We do not observe the year in which homes were purchased. New homeowners are approximated as

late mortgage payment (Table 6). We plot the relationship between late payments and DSTI using two approaches: (1) incorporating both DSTI and its square in a regression, and (2) employing linear splines at 10% intervals. Figure 8 displays the model predictions (estimated with person fixed effects), both of which suggest a small effect at lower DSTI levels and a pronounced, disproportionate rise in late payments with higher DSTI.

Building on this, we study the interaction of DSTI and unemployment. Our research question is whether a higher DSTI amplifies the effect of unemployment on late mortgage payments. There are two channels: the pre-unemployment DSTI level and the increase in DSTI due to reduced income during unemployment. Figure 9 shows the relevance of the latter - unemployment is associated with a higher DSTI, which increases in the first years of unemployment.

We estimate a model with full time variation of income including the effect over the course of unemployment spells. Figure 10 displays the prediction separately for unemployed and employed persons. It suggests that the impact of DSTI on late mortgage payments is more pronounced for unemployed individuals. It also suggests a non-linear effect of DSTI on late payments for both employed and unemployed individuals, with an amplifying effect at higher DSTI levels. For unemployed individuals, this amplifying effect persists up to a certain DSTI threshold, beyond which the effect does not increase further. Table 7 displays the related regression results. As depicted in column 2, the coefficient of the DSTI-unemployment interaction is insignificant in the linear specification with person fixed effects. However, when accounting for non-linearity with a squared DSTI term, the interaction effect becomes significant (column 3). We further explore the non-linearity by examining different DSTI brackets, with DSTI below 10% serving as the reference category (column 4). The coefficients of the interaction term for 10% to 40% DSTI are significantly positive while the coefficient is insignificant above 40% DSTI. The effect for unemployed individuals, who fall into the reference category with DSTI below 10%, is also insignificant. This underscores the non-linearity. The unemployment effect increases over-proportionally for higher DSTI until 40%, but no further for higher DSTI. Finally, we estimate the model using the unemployment month as a measure of unemployment (column 5). Here, all interactions are significant and the highest effects are observed for 30% to 40% DSTI and DSTI above 40%. To summarise, our results suggest that the risk of a mortgage loan measured by DSTI and unemployment positively interact with a non-linear amplifying effect on payment difficulties.[7]

persons living in a homeowner household with a mortgage who have not lived in a homeowner household with a mortgage in the previous wave but who still live in the same household.

[7]We consider two additional analyses as robustness checks. However, these are not reliable due to the limitation of insufficient variation in our data. First, a model with DSTI calculated with the last observation of the DSTI before the first unemployment year. This means that when the person becomes unemployed for the first time, it uses the DSTI of the previous period is used for all waves. The concern here is that the limited number of observations of unemployed mortgage debtors is significantly reduced, as it is necessary to exclude all individuals who are consistently unemployed or who are already unemployed at the time of their initial entry into the sample. Given this constraint, we have decided not to pursue this line of analysis. For similar reasons, we do not pursue a model that focuses on new buyers.

The non-linearity of the unemployment effect across DSTI dimensions aligns with our model with a critical expenditure threshold for debt service and other essential expenses. A high debt burden can push mortgage debtors above the critical threshold when faced with an income shock. The finding that high DSTI has an over-proportionate effect can also be explained by varying DSTI levels across different income groups, which in turn affects how unemployment influences late payments. Low-income households tend to have a higher DSTI (Figure 11) and also spend a larger portion of their income on daily living expenses (Deutsche Bundesbank, 2022). In other words, low-income households are closer to a subsistence level and hence less able to reduce their expenses. This reduces their ability to meet an income shock with a cut in spending to keep up with mortgage payments. Consistently, we observe that late payments of low-income debtors are more vulnerable to unemployment shocks (Figure 12). The results also holds in an econometric setup, the effect of unemployment on late payments is most pronounced with low income (regressions results not displayed).

To summarise, our analysis highlights the critical role of DSTI as a predictor of loan default risk. We also confirm that non-linearities exist and that the effect of DSTI on late payments is highest for unemployed persons when DSTI is in the range of 30% to 40%, (Table 7 column 4) thus providing support for a macroprudential policy that limits only high debt service levels. However, it is important to note that higher DSTI increases the probability of late payments independently of unemployment or the duration of unemployment (Table 6). This supports the liquidity hypothesis, as households under greater financial strain are more likely to encounter difficulties, even without becoming unemployed, likely due to other negative events not captured in our data.

5 Conclusion

We use a unique dataset for Germany, which reveals that unemployment has a strong and statistically significant effect on late payments, which we interpret as a proxy for default. In addition, we show that the effect of unemployment on late payments increases non-linearly in the debt service (DSTI) of households. According to our estimates, persons who lose their job are significantly more likely to make late payments on their mortgages if their debt service is between 30% and 40% of their net income. For low debt service ratios, the effect of unemployment is insignificant. We also show that the longer the unemployment duration, the more likely it is that households will miss a mortgage payment. These empirical results are novel for Germany and are relevant for financial stability and macroprudential regulation as our results imply that capping DSTI can significantly reduce the likelihood of household defaults.

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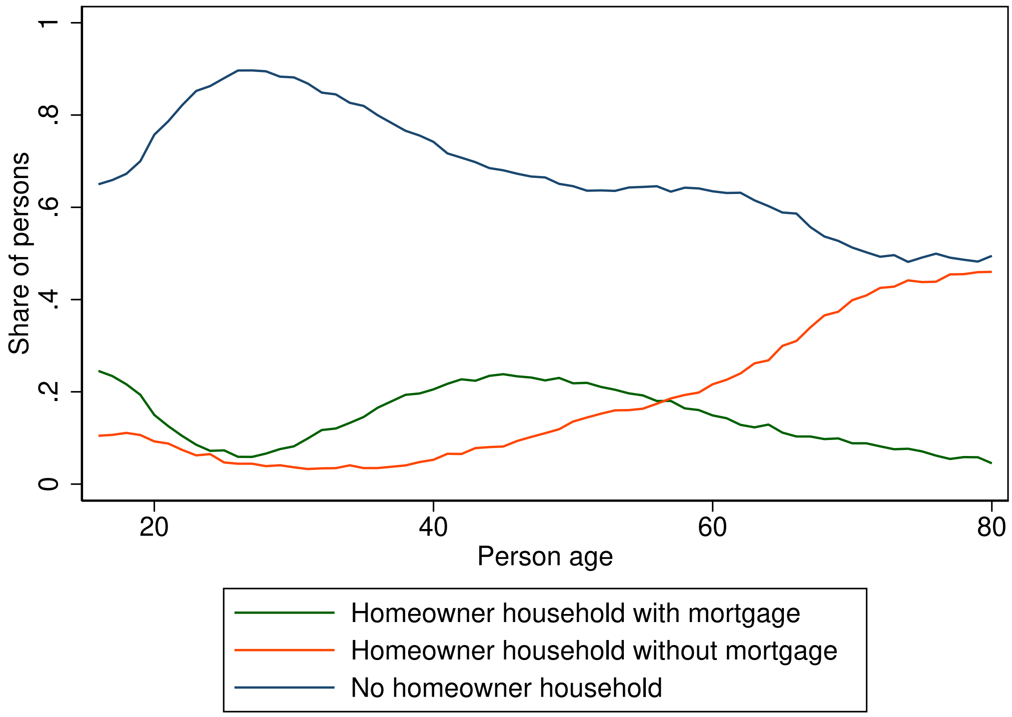
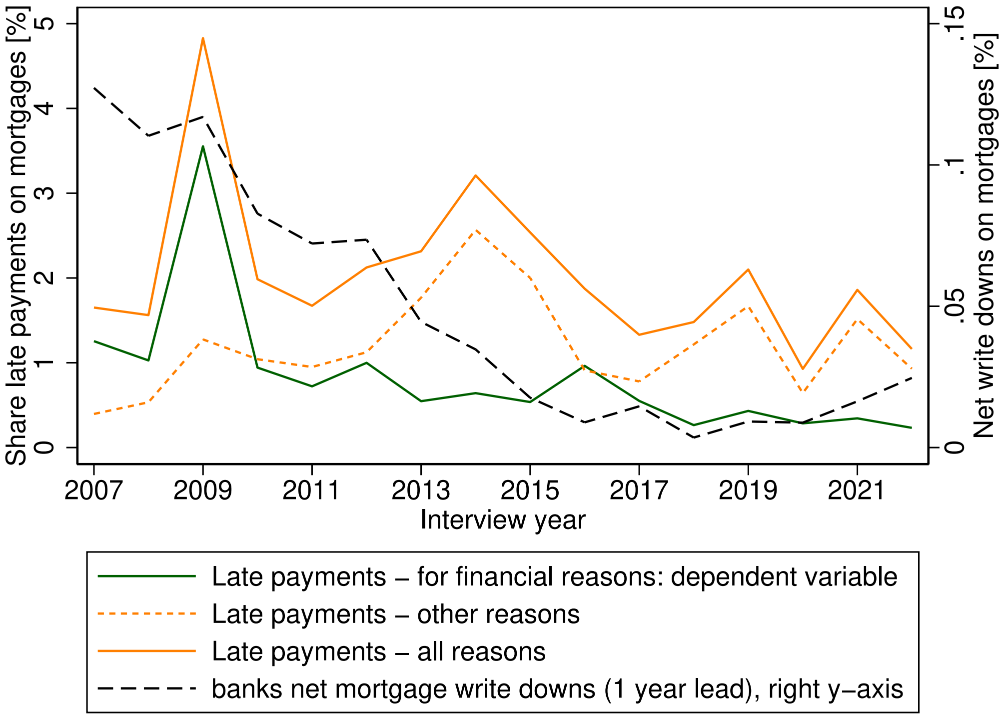
Figure 1: Share of persons in homeowner households with and without a mortgage by person age



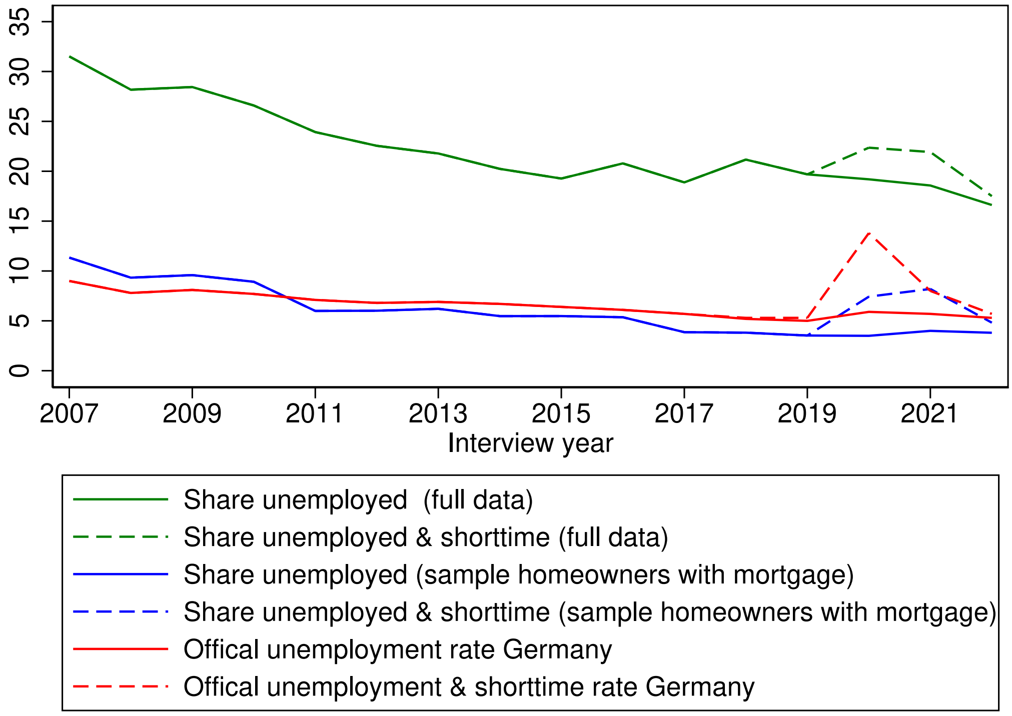
The graph shows (aggregated across survey waves by person age) the share of persons who are either living in homeowner households with a mortgage, homeowner households without a mortgage (i.e. debt free ownership) or households without owning a home, including renting households and households living rent-free in homes not-owned.

Figure 2: Share of late payments on mortgage loans, by reason



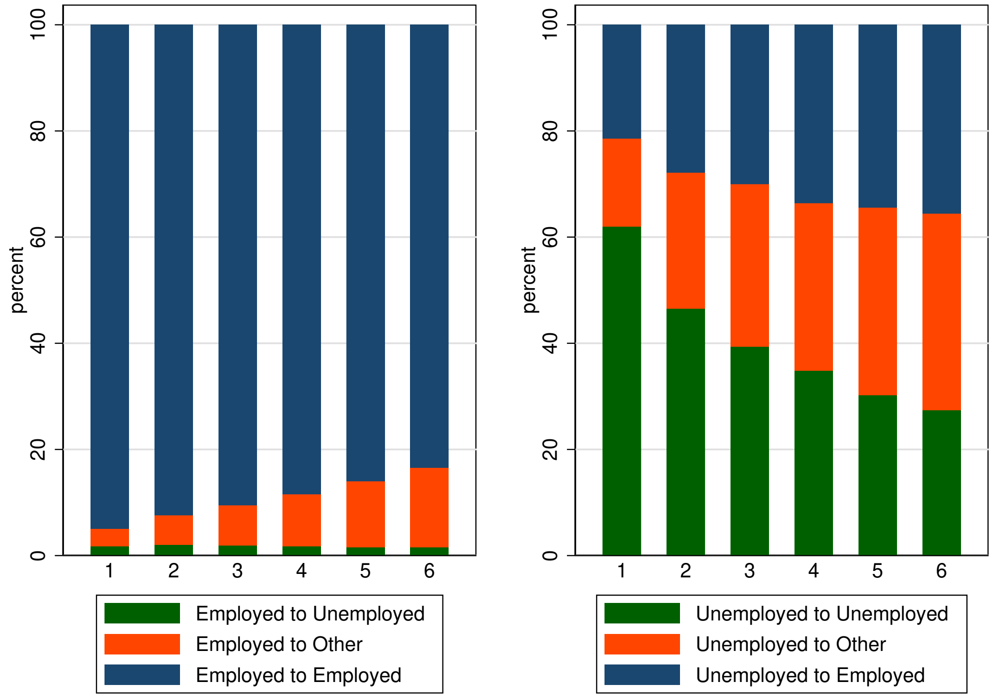
The graph shows the share of persons with a late payment on their mortgage by interview year. It distinguishes between late payments for financial reasons, our baseline dependent variable, and late payments for other reasons. Sample: persons in homeowner households with a mortgage. This is compared to the time series net write-down of mortgage loans to private not-self-employed households aggregated over German banks. Data set is Quarterly Borrower Statistics.

Figure 3: Share of unemployed persons over time (%)



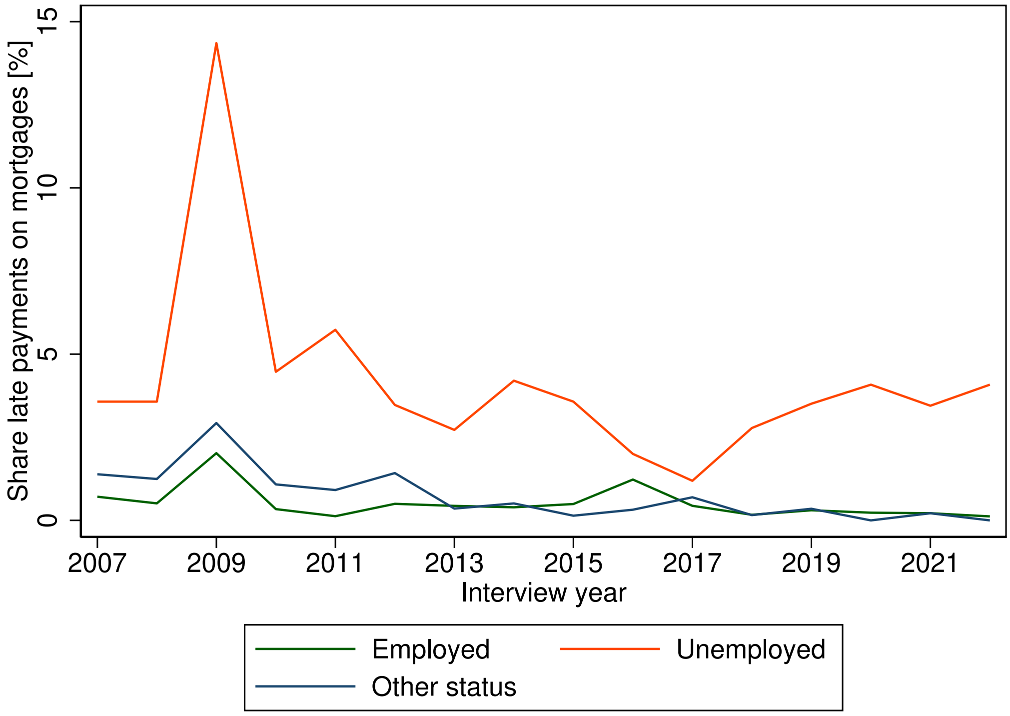
The graph shows the share of unemployed persons by survey year. The green line displays the share of unemployed persons in the full survey, i.e. homeowners with and without a mortgage loan as well as tenants and rent-free living. The blue line displays the share of unemployed persons among homeowners with a mortgage loan, the sample of all analyses in the paper. The red line displays the official unemployment rate of Germany for comparison. The dashed lines includes persons receiving short-time work allowance during the Covid-19 pandemic, a wage subsidy with a temporary reduction of working hours The official unemployment rate and short-time work allowance rate are provided by the Federal Statistical Office.

Figure 4: Transition probability for the employment status of employed and unemployed persons



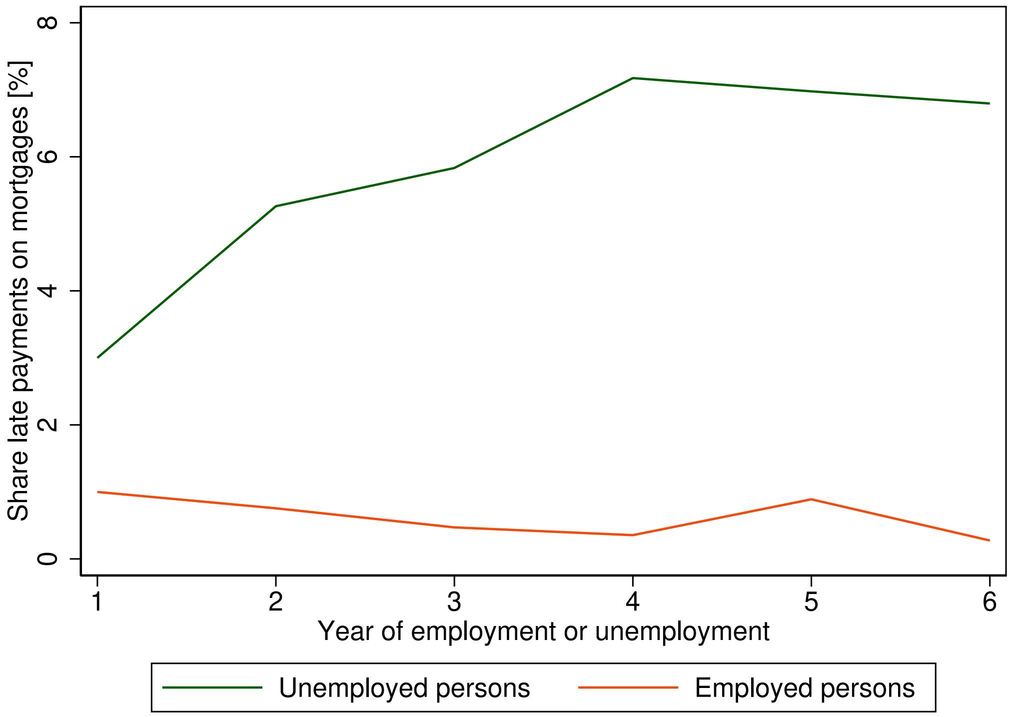
The graph shows across waves the share of persons that are employed, unemployed or have other status in year 1 to 8 conditional on being either employed (LHS) or unemployed (RHS) in year 0. The number of years before are displayed on the x-axis. Sample: persons in homeowner households with a mortgage.

Figure 5: Late payments on mortgage loans over time by employment status (%)



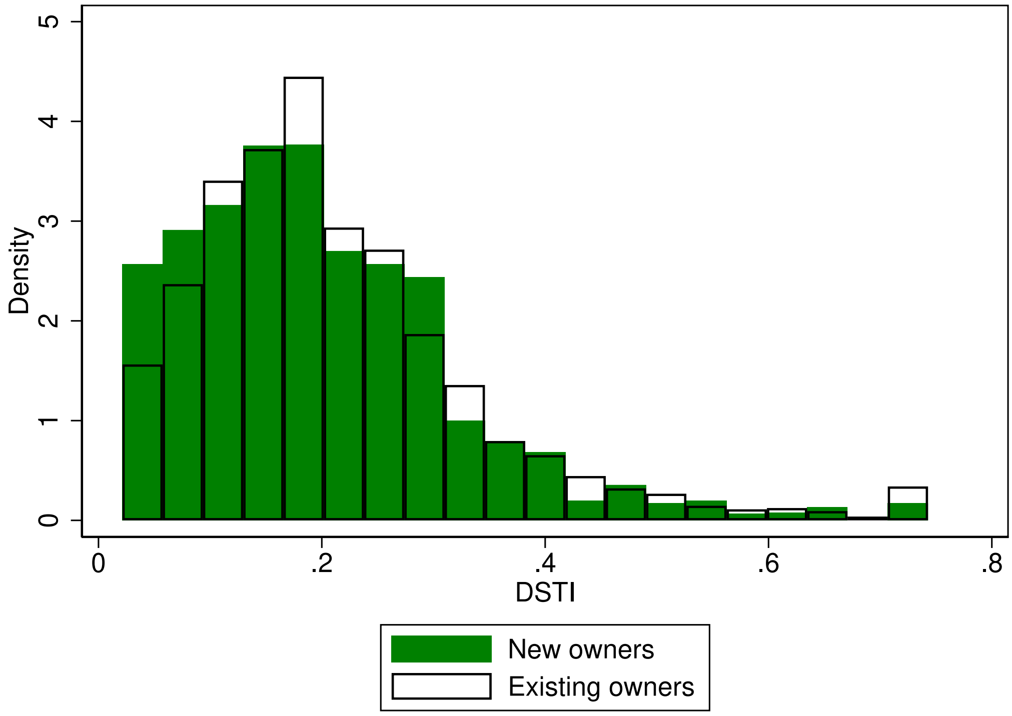
The graph shows the share of persons with a late payment on their mortgage by survey year. The three categories are employed persons, unemployed persons or other status such as retired or in education. Sample: persons in homeowner households with a mortgage.

Figure 6: Late payments on mortgage loans by year of employment or year of unemployment(%)



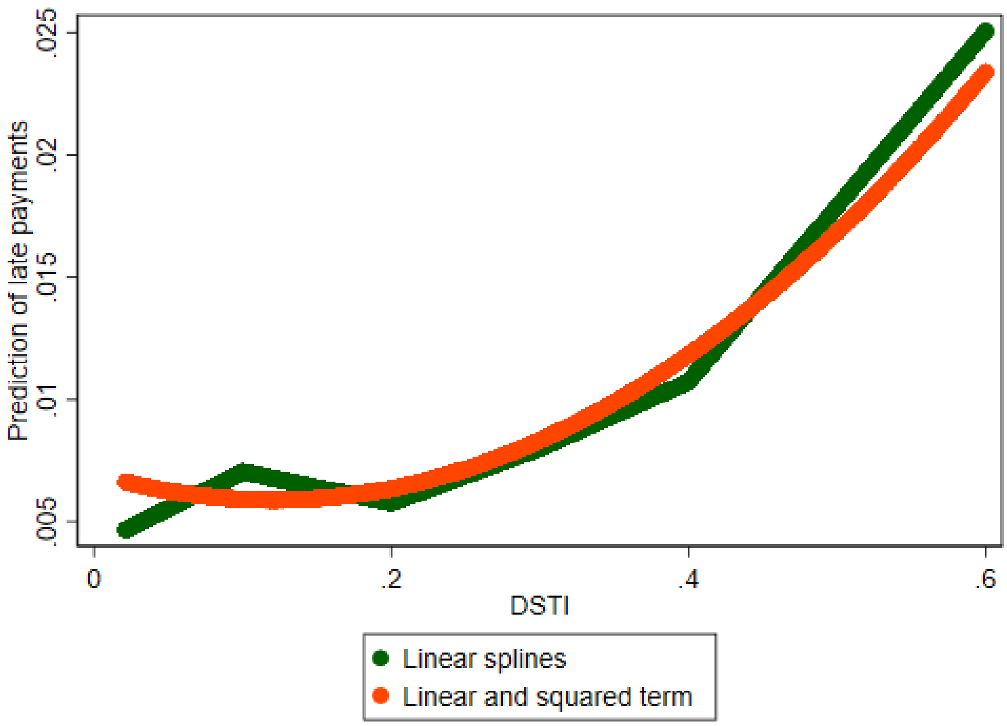
The graph shows the share of persons with a late payment on their mortgage by year of length of the current employment status. The two categories are either employed persons (employment length) and unemployed persons (unemployment length). The length is calculated using the interview month and the month of unemployment declaration or the start of employment. The graph starts at 1, because 1 means within the first year, i.e. unemployed or employed between 0 and 12 months. Only length up to six years is displayed because only for this length there are at least 100 observations by unemployment year. Employment length is the duration with the current employer. Sample: persons in homeowner households with a mortgage.

Figure 7: Histogram DSTI of homeowners with loans



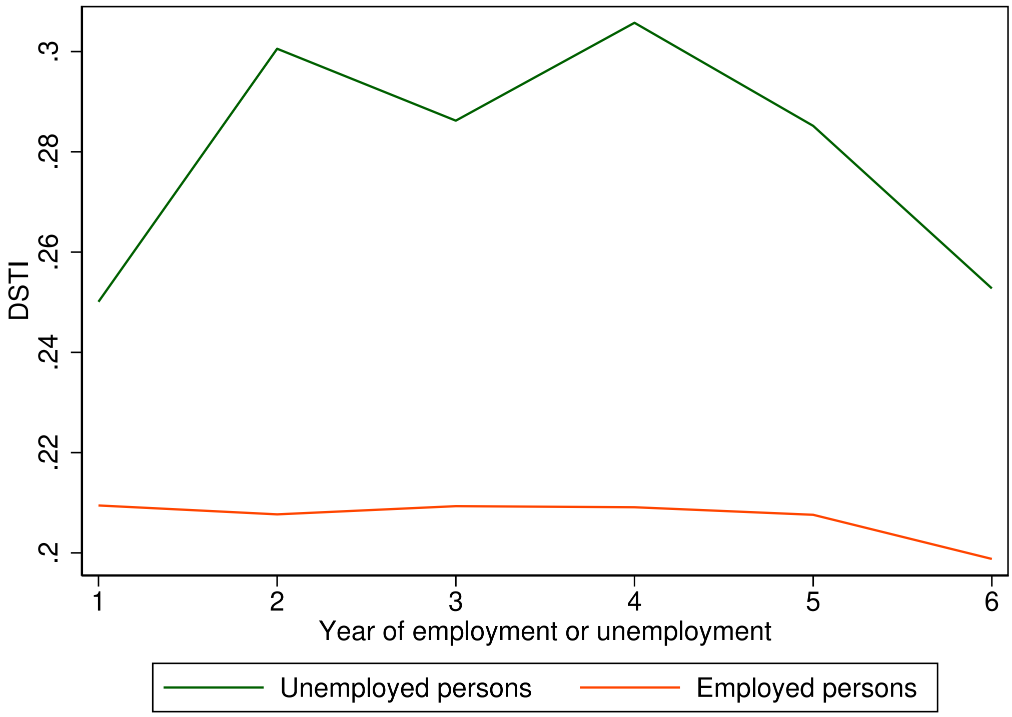
The graph shows a histogram of debt service to income (DSTI) ratio. We calculate DSTI as the monthly payment for interest and repayment of mortgage loans divided by monthly household net income. We truncate DSTI at 1% and 99% to remove outliers. The two categories are either new home owners with a mortgage and existing owners with a mortgage. New owners are approximated as those persons that did not indicate to live in homeowner household with a mortgage in the previous survey wave. Sample: persons in homeowner households with a mortgage.

Figure 8: Estimated relationship between late payments on mortgages and DSTI



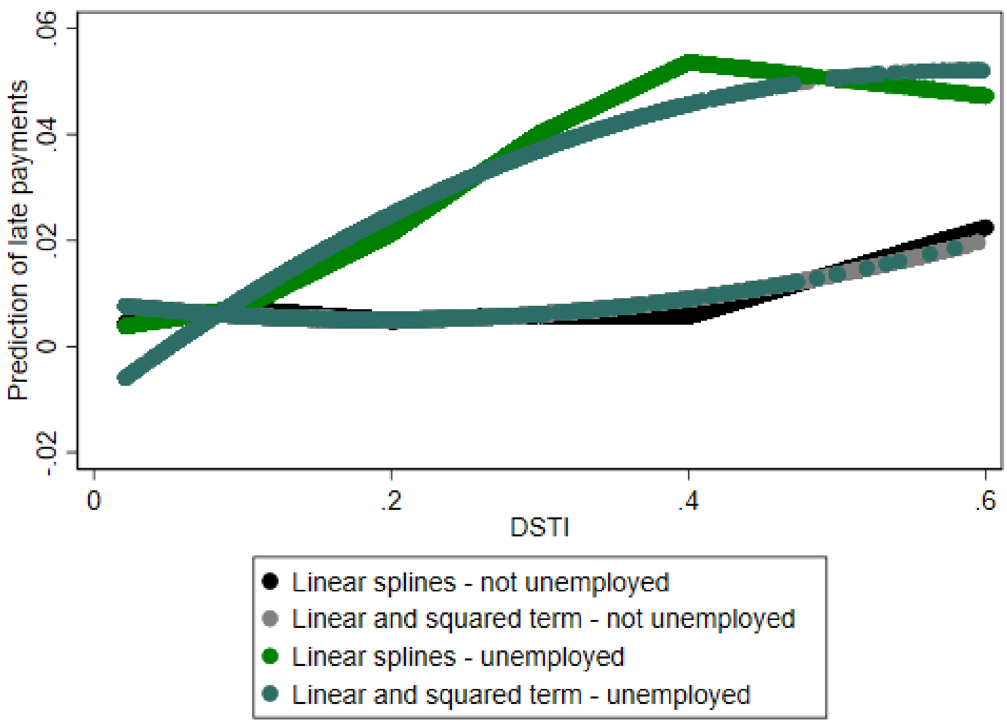
The graph shows the estimated relationship between late payments on mortgages and debt service to income ratio (DSTI). We calculate DSTI as the monthly payment for interest and repayment of mortgage loans divided by monthly household net income. We truncate DSTI at 1% and 99% to remove outliers. The displayed prediction is based on two different models of a non-linear relationship, with a linear term of DSTI and squared DSTI and employing linear splines at 10% intervals. The estimates are derived in linear regressions of late payments on DSTI with person and time fixed effects without control variables. Sample: persons in homeowner households with a mortgage.

Figure 9: DSTI of homeowners with loans by year of employment or year of unemployment



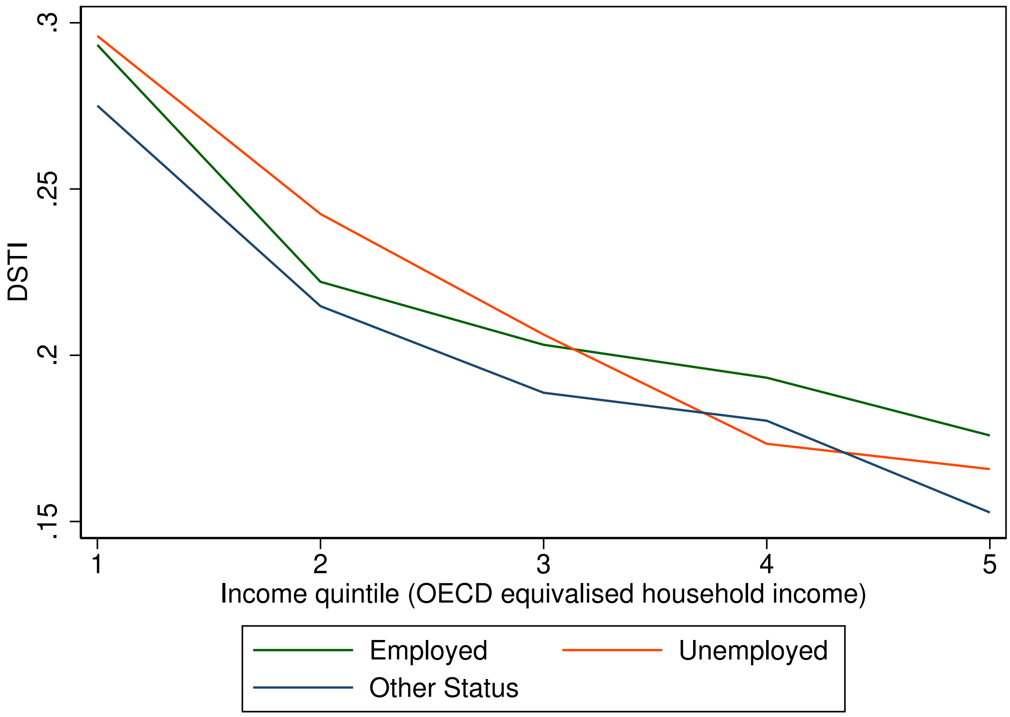
The graph shows the mean DSTI by year of length of the current employment status. We calculate DSTI as the monthly payment for interest and repayment of mortgage loans divided by monthly household net income. We truncate DSTI at 1% and 99% to remove outliers. The two categories are either employed persons (employment length) and unemployed persons (unemployment length). The graph starts at 1, because 1 means within the first year, i.e. unemployed or employed between 0 and 12 months. Only length up to nine years is displayed. Sample: persons in homeowner households with a mortgage.

Figure 10: Estimated relationship between late payments on mortgages and DSTI, not unemployed vs. unemployed persons



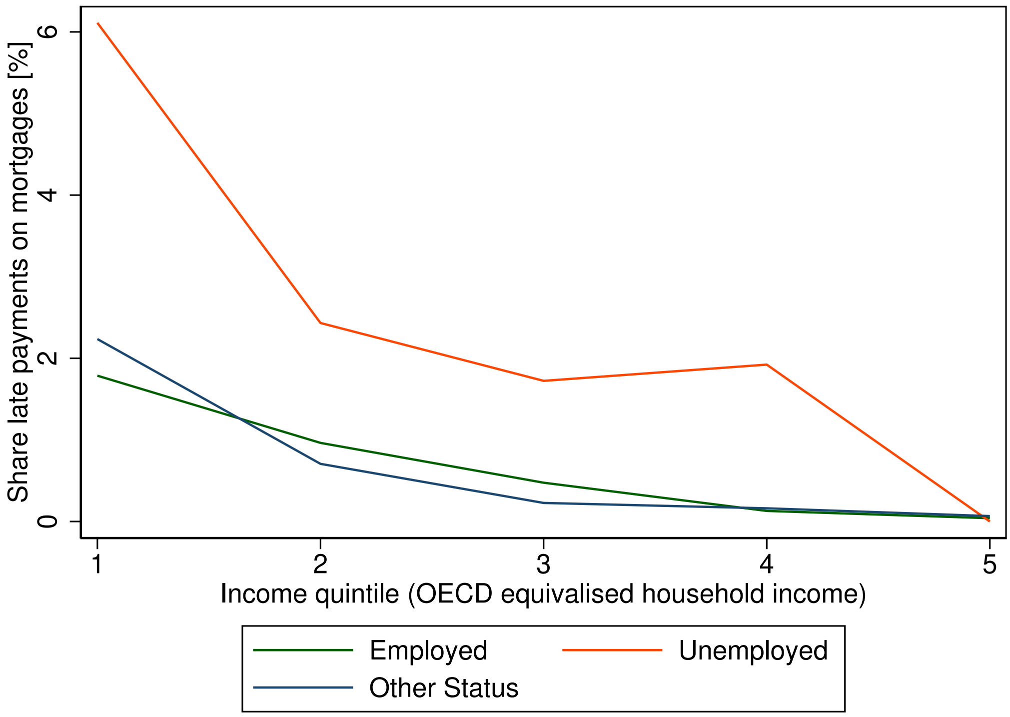
The graph shows the estimated relationship between late payments on mortgages and debt service to income ratio (DSTI). We calculate DSTI as the monthly payment for interest and repayment of mortgage loans divided by monthly household net income. We truncate DSTI at 1% and 99% to remove outliers. The predictions are based on (1) a non-linear model with the terms DSTI and squared DSTI both interacted with the unemployment dummy or (2) linear splines of DSTI interacted with the unemployment dummy. The estimates are derived in linear regressions with person and time fixed effects without control variables. The prediction is either made for unemployment persons or non-unemployed persons. Sample: persons in homeowner households with a mortgage.

Figure 11: Relationship between DSTI ratios and income quintiles, unemployed vs. employed vs. other status



The graph shows the average DSTI by income quintile. We calculate DSTI as the monthly payment for interest and repayment of mortgage loans divided by monthly household net income. We truncate DSTI at 1% and 99% to remove outliers. Income is the OECD scale modified income which adjusts for household size provided in the data set. It is computed as household net income weighted by household size with the first (at least 15-year-old) person in the household to have a need weight of 1.0. All other persons aged 15 receive a need weighting of 0.5; persons up to and including 14 are given a persons up to and including 14 are included with a weight of 0.3. The three categories are employed persons, unemployed persons or other status such as retired or in education. Sample: persons in homeowner households with a mortgage.

Figure 12: Relationship between late payments mortgage loans and income quintiles, unemployed vs. employed vs. other status



The graph shows the share of persons with a late payment on their mortgage by income quintile. Income is the OECD scale modified income which adjusts for household size provided in the data set. It is computed as household net income weighted by household size with the first (at least 15-year-old) person in the household to have a need weight of 1.0. All other persons aged 15 receive a need weighting of 0.5; persons up to and including 14 are given a persons up to and including 14 are included with a weight of 0.3. The three categories are employed persons, unemployed persons or other status such as retired or in education.

Table 1: Sample overview - Number of persons with and without a mortgage by wave

Wave	Interview year	Without mortgage	With mortgage	N
1	2006/2007	15,774	3,180	18,954
2	2007/2008	10,136	2,351	12,487
3	2008/2009	11,159	2,280	13,439
4	2010	9,753	2,015	11,768
5	2011	12,976	2,631	15,607
6	2012	12,218	2,401	14,619
7	2013	12,049	2,376	14,425
8	2014	11,236	2,181	13,417
9	2015	11,156	2,049	13,205
10	2016	10,723	1,868	12,591
11	2017	11,414	2,180	13,594
12	2018	11,242	1,891	13,133
13	2019	10,281	1,619	11,900
14	2020	8,809	1,401	10,210
15	2021	9,816	1,452	11,268
16	2022	8,977	1,290	10,267
Total		177,719	33,165	210,884

This table gives an overview of the number of interviewed persons included in the German household panel data set Labour Market and Social Security (PASS) provided by the German Federal Labour Employment agency. We use the version available in 2023 with 16 waves. Access is available for labour market research on request.

Table 2: Summary statistics

Variable	Mean	P25	Median	P75	N
Late payment mortgage loan	0.01	0.00	0.00	0.00	33,165
Unemployed	0.06	0.00	0.00	0.00	32,977
Unemployment Month	2.41	0.00	0.00	0.00	32,867
Other Status	0.34	0.00	0.00	1.00	32,974
Female	0.51	0.00	1.00	1.00	33,165
Age (years)	44.39	35.00	46.00	55.00	33,114
Education (years)	12.65	10.50	11.50	14.50	31,158
No. children in HH	0.92	0.00	1.00	2.00	32,964
Married	0.68	0.00	1.00	1.00	32,357
Unmarried partner in HH	0.07	0.00	0.00	0.00	33,165
Persons in HH	3.20	2.00	3.00	4.00	33,165
Debt service per month in 1k EUR	0.62	0.31	0.55	0.83	33,165
Household income per month in 1k EUR	3.43	2.20	3.10	4.20	32,681
Debt service to income ratio (DSTI)	0.21	0.12	0.19	0.27	31,022
Financial assets in 1k EUR	18.05	0.50	7.50	15.00	31,492
HH income OECD scale per month in 1k EUR	1.77	1.14	1.60	2.17	33,165

This table reports unweighted summary statistics at the person level from the Panel Labour Market and Social Security (PASS). The sample is persons living in a household with an outstanding mortgage. Variables are defined in the text in Section 2. We truncate DSTI and unemployment months at 1% and 99% to remove outliers.

Table 3: Mean of main variables by late payment

Variable	Late payments = 1	Late payments = 0
Unemployed	0.33	0.06
Unemployment Month	14.55	2.30
Other Status	0.31	0.34
Female	0.47	0.51
Age (years)	41.50	44.41
Education (years)	11.50	12.66
No. children in HH	1.08	0.92
Married	0.50	0.68
Unmarried partner in HH	0.05	0.07
Persons in HH	3.36	3.20
Debt service per month in 1k EUR	0.59	0.62
Household income per month in 1k EUR	1.75	3.45
DSTI	0.37	0.21
Financial assets in 1k EUR	2.08	18.20
HH income OECD scale per month in 1k EUR	0.88	1.78

This table reports the unweighted mean split by whether the person reports a late payment of his mortgage loan or not. Statistics are at the person level from the Panel Labour Market and Social Security (PASS). The sample is persons living in a household with an outstanding mortgage. Variables are defined in the text in Section 2. We truncate DSTI and unemployment months at 1% and 99% to remove outliers.

Table 4: Baseline regression results

VARIABLES	1 Late paym	2 Late paym	3 Late paym	4 Late paym	5 Late paym
Unemployed	0.037***	0.019***	0.020***		
	0.0052	0.0067	0.0078		
Lag Unemployed			0.013**		
			0.0056		
Unemployment Month				0.00097***	
				0.00029	
Sq Unemployment Month				-4.9e-06**	
				2.5e-06	
1st year UE					0.0040
					0.0074
2nd year UE					0.021
					0.016
3rd year UE					0.040**
					0.019 9
4th year UE					0.040*
					0.022
5th year+ UE					0.055***
					0.016
Other Status	0.0025*	-0.00026	-0.0055*	-1.7e-06	0.00067
	0.0014	0.0032	0.0031	0.0031	0.0032
Lag Other Status			0.0054*		
			0.0029		
Observations	30,579	27,810	22,129	27,730	27,825
R-squared	0.021	0.339	0.367	0.340	0.340
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Person FE	No	Yes	Yes	Yes	Yes

*p<.05; **p<.01; ***p<.001

This table reports results of linear regressions on a person-wave level using the Stata command reghdfe. The dependent variable is late payments of mortgage loans for financial reasons. Singleton observations excluded, standard errors clustered by person. Unemployment and unemployment months are measured on the person level. Unemployed is a dummy whether the person is unemployed. Unemployed Month is the number of unemployment months of the person. We truncate unemployment months at 1% and 99% to remove outliers. Control variables are female (only in column 1), age of the person in years, years of education, number of children in the household, married, unmarried partner living in the same households and persons living in the household. The sample is persons living in a household with an outstanding mortgage.

Table 5: Unemployed on a household level: regression results

VARIABLES	(1) Late paym	(2) Late paym	(3) Late paym	(4) Late paym
Unemployed_HH	0.016***	0.0088**	0.019***	
	(0.0038)	(0.0036)	(0.0042)	
ALG2	0.031***	0.020**		
	(0.0057)	(0.0090)		
Lag Unemployed_HH			0.0088***	
			(0.0032)	
Unemployed Month_HH				0.00030**
				(0.00012)
Other Status_HH	-0.00029	-0.00021	-0.0017	-0.00068
	(0.0013)	(0.0020)	(0.0020)	(0.0022)
Lag Other Status_HH			0.00040	
			(0.0020)	
Observations	30,693	27,916	22,236	27,925
R-squared	0.026	0.340	0.369	0.340
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Person FE	No	Yes	Yes	Yes

Linear regression
SE clustered by pnr
*p<.05; **p<.01; ***p<.001

This table reports results of linear regressions on a person-wave level using the Stata command reghdfe. The dependent variable is late payments of mortgage loans for financial reasons. Singleton observations excluded, standard errors clustered by person. Unemployment is measured on the household level, Unemployed_HH is a dummy whether at least on person in the household is unemployed. Unemployed Month_HH is the total number of unemployment months of persons living in the household. We truncate unemployment months at 1% and 99% to remove outliers. Control variables are age of the person in years, years of education, number of children in the household, married, unmarried partner living in the same households and persons living in the household. The sample is persons living in a household with an outstanding mortgage.

Table 6: Late payments and DSTI: regression results

VARIABLES	(1) Late paym	(2) Late paym	(3) Late paym	(4) Late paym	(5) Late paym	(6) Late paym
DSTI	0.077***	0.036***	-0.038*	-0.026		
	(0.010)	(0.012)	(0.021)	(0.025)		
Squared DSTI			0.19***	0.090**		
			(0.046)	(0.046)		
DSTI between 10% and 20%					0.0033***	0.0025
					(0.0010)	(0.0017)
DSTI between 20% and 30%					0.0024**	-0.00023
					(0.0010)	(0.0021)
DSTI between 30% and 40%					0.012***	0.0039
					(0.0023)	(0.0030)
DSTI above 40%					0.036***	0.012**
					(0.0050)	(0.0048)
Other Status	-0.0028*	-0.0046	-0.0025*	-0.0043	-0.0028*	-0.0042
	(0.0015)	(0.0034)	(0.0015)	(0.0034)	(0.0015)	(0.0034)
Female	-0.0022*		-0.0024*		-0.0024*	
	(0.0013)		(0.0013)		(0.0013)	
Age (years)	0.000098*	-0.000018	0.000031	-0.000061	0.000036	-0.00011
	(0.000057)	(0.0026)	(0.000056)	(0.0026)	(0.000056)	(0.0026)
Education (years)	-0.0011***	0.00031	-0.0011***	0.00031	-0.0011***	0.00037
	(0.00024)	(0.0017)	(0.00024)	(0.0017)	(0.00024)	(0.0017)
No. children in HH	0.0030**	-0.00026	0.0036***	0.00014	0.0036***	0.00032
	(0.0013)	(0.0028)	(0.0013)	(0.0028)	(0.0013)	(0.0028)
Married	-0.013***	-0.0038	-0.012***	-0.0035	-0.012***	-0.0039
	(0.0023)	(0.0084)	(0.0022)	(0.0084)	(0.0023)	(0.0085)
Unmarried partner in HH	-0.010***	-0.0040	-0.0095***	-0.0039	-0.010***	-0.0045
	(0.0027)	(0.0065)	(0.0027)	(0.0065)	(0.0028)	(0.0066)
Persons in HH	-0.00022	-0.0034	-0.00066	-0.0038*	-0.00076	-0.0040*
	(0.0010)	(0.0021)	(0.0010)	(0.0021)	(0.0010)	(0.0021)
Observations	28,663	26,082	28,663	26,082	28,663	26,082
R-squared	0.023	0.335	0.026	0.335	0.022	0.335
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	No	Yes	No	Yes	No	Yes

Linear regression
SE clustered by pnr
*p<.05; **p<.01; ***p<.001

This table reports results of linear regressions on a person-wave level using the Stata command reghdfe. The dependent variable is late payments of mortgage loans for financial reasons. Singleton observations excluded, standard errors clustered by person. We calculate DSTI as the monthly payment for interest and repayment of mortgage loans divided by monthly household net income. We truncate DSTI at 1% and 99% to remove outliers. The sample is persons living in a household with an outstanding mortgage.

Table 7: Late payments, time-varying DSTI and unemployment: Regressions results

VARIABLES	(1) Late paym	(2) Late paym	(3) Late paym	(4) Late paym	(5) Late paym
Unemployed	-0.0023	0.0051	-0.020	-0.012	
	(0.0088)	(0.011)	(0.016)	(0.011)	
Unemployment Month					-0.000065
					(0.00017)
DSTI	0.052***	0.024**	-0.047*		
	(0.0086)	(0.012)	(0.025)		
Unemployed#DSTI	0.14***	0.059	0.26**		
	(0.039)	(0.054)	(0.12)		
Squared DSTI			0.11**		
			(0.049)		
Unemployed#Squared DSTI			-0.29		
			(0.19)		
DSTI between 10% and 20%				0.00090	0.0011
				(0.0014)	(0.0015)
DSTI between 10% and 20%#Unemployed				0.032**	
				(0.014)	
DSTI between 20% and 30%				-0.0022	-0.0014
				(0.0019)	(0.0020)
DSTI between 20% and 30%#Unemployed				0.031**	
				(0.014)	
DSTI between 30% and 40%				-0.0013	0.00018
				(0.0028)	(0.0029)
DSTI between 30% and 40%#Unemployed				0.065***	
				(0.018)	
DSTI above 40%				0.0088*	0.0088*
				(0.0048)	(0.0049)
DSTI above 40% #Unemployed				0.035	
				(0.024)	
DSTI between 10% and 20%#Unemployment Month					0.00074***
					(0.00028)
DSTI between 20% and 30%#Unemployment Month					0.00046*
					(0.00027)
DSTI between 30% and 40%#Unemployment Month					0.0010***
					(0.00033)
DSTI above 40%#Unemployment Month					0.00096**
					(0.00044)
Other Status	0.0019	-0.00055	-0.00033	-0.000042	-0.00052
	(0.0015)	(0.0033)	(0.0033)	(0.0033)	(0.0032)
Observations	28,649	26,068	26,068	26,068	25,995
R-squared	0.035	0.336	0.337	0.337	0.339
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Person FE	No	Yes	Yes	Yes	Yes

Linear regression
SE clustered by pnr
*p$<$.05; **p$<$.01; ***p$<$.001

This table reports results of linear regressions on a person-wave level using the Stata command reghdfe. The dependent variable is late payments of mortgage loans for financial reasons. Singleton observations excluded, standard errors clustered by person. Unemployment and unemployment months are measured on the person level. We calculate DSTI as the monthly payment for interest and repayment of mortgage loans divided by monthly household net income. We truncate DSTI and unemployment months at 1% and 99% to remove outliers. Control variables are age of the person in years, years of education, number of children in the household, married, unmarried partner living in the same households and persons living in the household. The sample is persons living in a household with an outstanding mortgage.