National Audit Office

Estimating the cost of problem debt to the public purse

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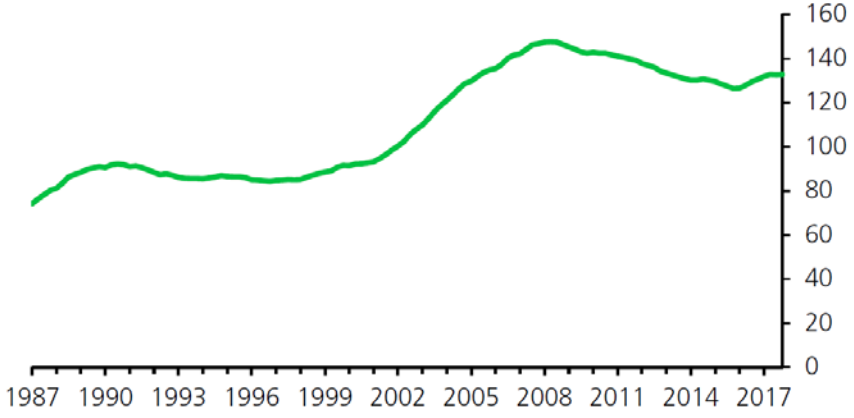
Motivation

- There is £1.8tn of personal debt in total in the UK.
- The Money Advice Service estimates that 8.2m people are over-indebted by an estimated £28bn
- The UK's debt to income ratio has increased from 127% in 2015 to 133% in 2017

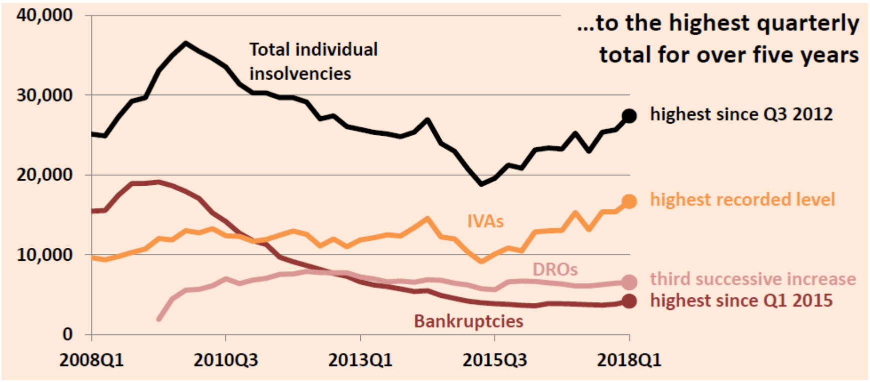
Household debt, % of disposable income



Sources: ONS, series NIWK (debt) and rolling 4-quarter total of RPHA (income)

- The number of total individual insolvencies in England and Wales have reached their highest level since 2012, nearly 50% higher than in 2015

Insolvencies

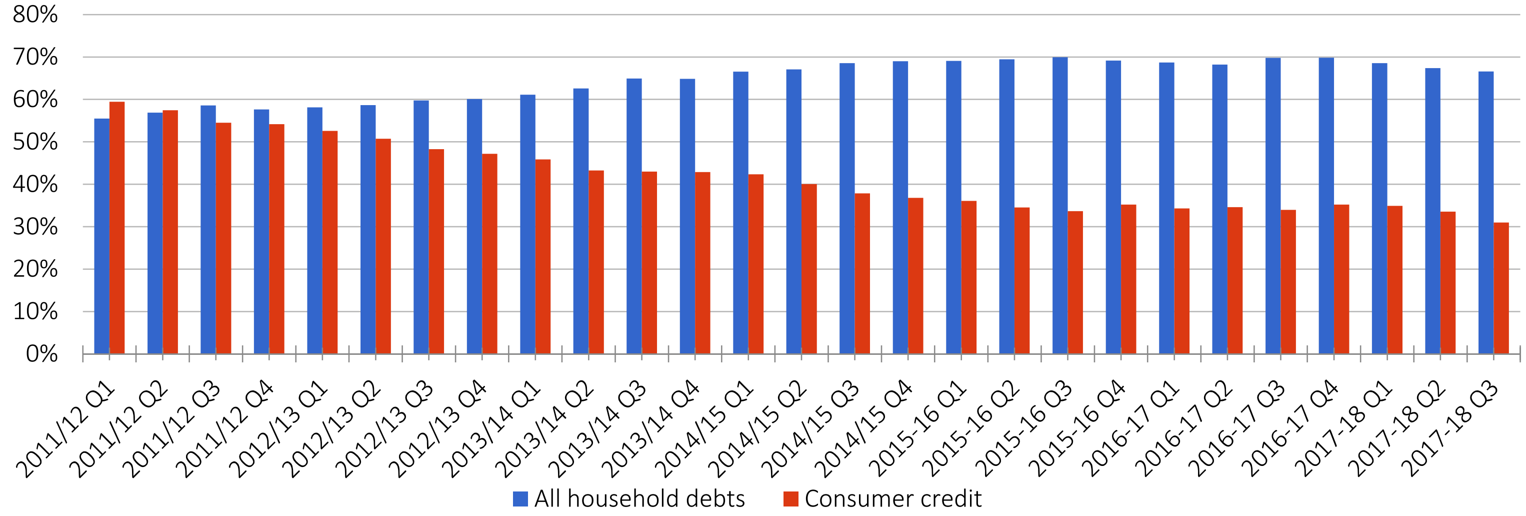


Source: FT

Motivation

- People are increasingly struggling with government and utility debts, compared with consumer credit products

Type of debts presented by people to Citizens Advice



Note: “All household debts” refers to household arrears such as utilities, rent, council tax, etc. and excludes consumer credit

- Government monitors and regulates consumer credit extensively, but does not have a comprehensive picture of other types of indebtedness
- Government does not know what over-indebtedness costs the public purse through increased use of government services

Motivation

- Given the large and growing role of debt in the UK economy, and of government in the UK debt sector, it is increasingly important to understand how debt impacts the public purse.

- **Direct impacts**: Where government holds the debt, there is a direct cost to government both through the cost of enforcement action and through debt never recovered. This is accounted for.

- **Indirect impacts**: People who get into problem debt may well need to make use of government services – the social safety net.

- The indirect costs to the public purse through the cost of additional services, e.g social housing, benefits or health – these are not known or accounted for.

Objective of analysis

In this analysis, we provide the first estimates of the size of this indirect channel.

In particular, we estimate the effect of being in ‘problem’ debt on:

- Housing status
- Employment status
- Benefit receipt

And hence estimate a cost to the public purse of ‘problem’ debt through these channels.

This presentation will focus on the housing and employment questions, but the other question is analogous and addressed by similar models.

Outline

- Literature
- Data
- Descriptives
- Empirical strategy
- Results
- Further analysis

Literature

Considerable work has already been done to understand the size of the debt sector in the UK and the impacts it has...

On the economy as a whole

- Harari, 2018: General trends in household debt
- Finds that household debt had risen until the financial crisis of 2008 when banks were reluctant to lend, and since 2016 is once again rising

On people, particularly in low-income households

- Hood, Joyce, and Sturrock, 2018
- Identifies households under debt servicing pressure across the income distribution
- In the bottom decile, just 27% hold sufficient financial assets to clear their debts

We contribute by modelling the wider, indirect costs that debt can have through the use of the social safety net.

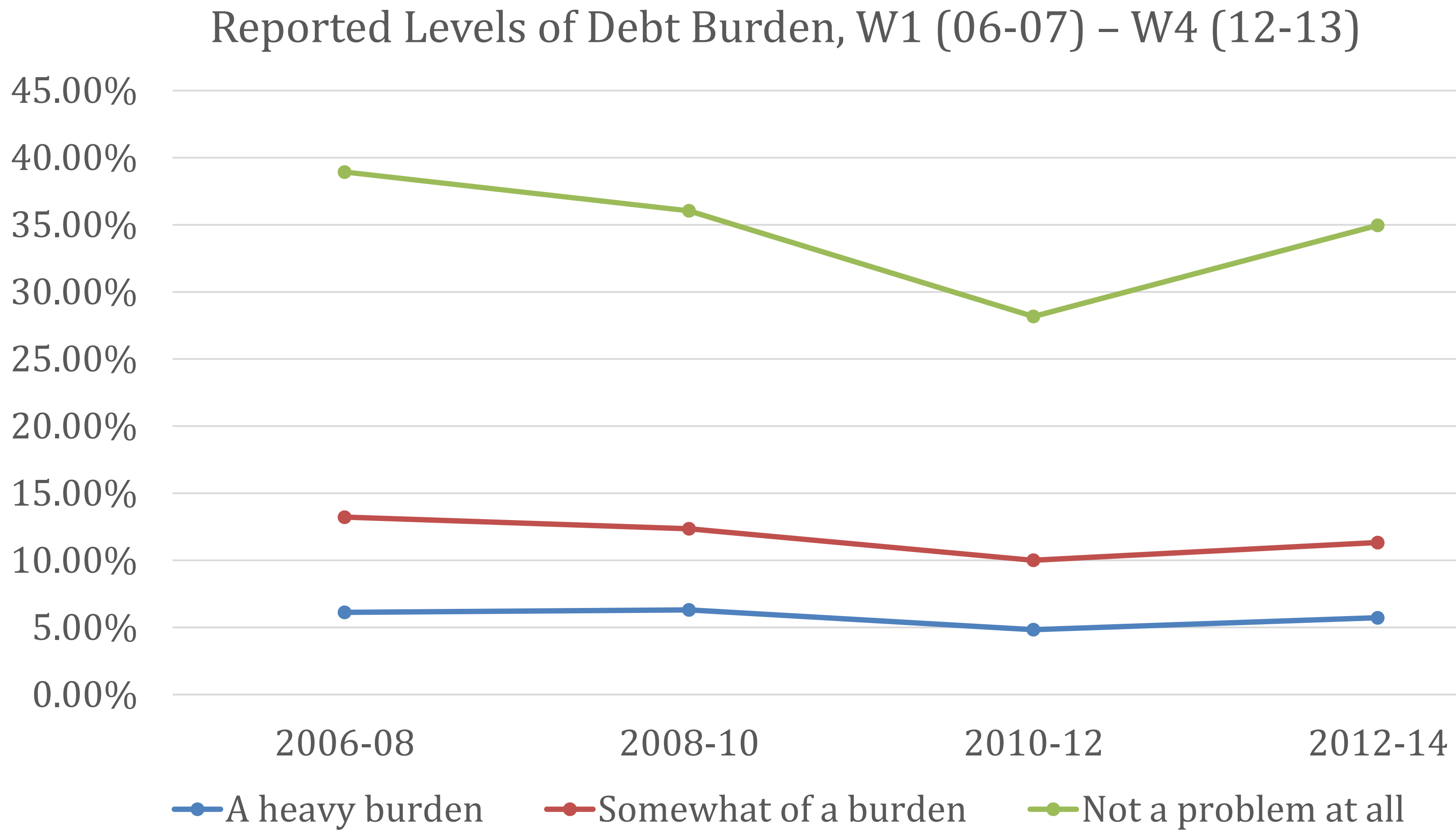
The data

Main data source: Wealth and Assets Survey

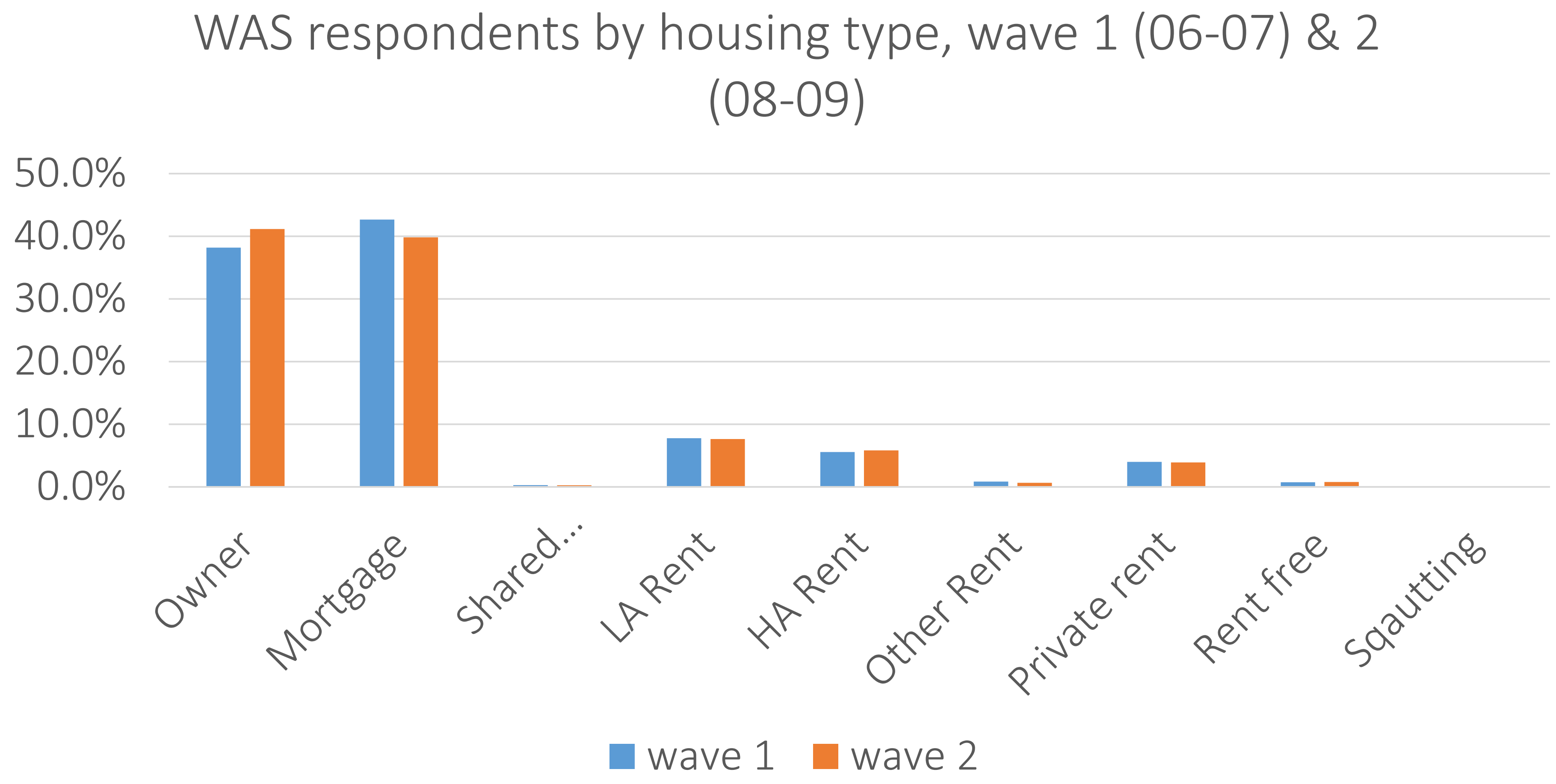
- Longitudinal dataset (5 waves, 2006-2014)
- Offers the ability to trace out the impact of debt over time and to account for persistence in outcomes like housing status
- Information on (subjective) debt burden as well as demographics (e.g. sex, age, qualifications) and several economic variables of interest
- Large sample size (wave 5 approx. 18,000) and good response rates mean we can have reliable estimates even for relatively small subgroups (e.g. social renters)

Descriptives – Debt

Explanatory variable of interest is ‘problem debt’: respondents who felt their debt burden was somewhat of a burden, or a heavy burden



Descriptives – Housing



Descriptives – Housing

Stochastic matrix, housing, w1-w2

- Shows the percentage chance of moving from one state to another, given the initial state in the first period.

- Purely descriptive

		Wave 2							
		Owner	Mortgage	Shared ownership	LA rented	HA rented	Private rented	Other rented	Rent free
Wave 1	Owner	96.67	2.36	0.04	0.23	0.15	0.1	0.07	0.38
	Mortgage	10.03	88.38	0.19	0.09	0.07	0.88	0.12	0.22
	Shared ownership	6.78	10.17	72.88	3.39	3.39	1.69	1.69	0
	LA rented	0.54	0.98	0.05	86.77	10.85	0.65	0.11	0.05
	HA rented	0.08	0.69	0.08	10.31	86.62	1.54	0.46	0.23
	Private rented	1.58	9.8	0.2	1.49	3.66	79.01	3.37	0.89
	Other rented	2.78	5.56	0	2.31	2.78	33.8	50	2.78
	Rent free	7.22	3.09	0	1.03	0.52	2.58	8.25	77.32

Descriptives – Housing

Stochastic matrix, housing, w1-w2

- This matrix compares wave 2 housing status with wave 1 housing status

- Focus on LA & HA rented probabilities

		Wave 2							
		Owner	Mortgage	Shared ownership	LA rented	HA rented	Private rented	Other rented	Rent free
Wave 1	Owner	96.67	2.36	0.04	0.23	0.15	0.1	0.07	0.38
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Descriptives – Housing

Stochastic matrix, housing, w1-w2

- This matrix compares wave 2 housing status with wave 1 housing status
- Note the probabilities are high on the diagonal: These are people who do not change housing status (mostly!)

Wave 2

Wave 1	Owner	Mortgage	Shared ownership	LA rented	HA rented	Private rented	Other rented	Rent free
Owner	96.67	2.36	0.04	0.23	0.15	0.1	0.07	0.38
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Other rented	2.78	5.56	0	2.31	2.78	33.8	50	2.78
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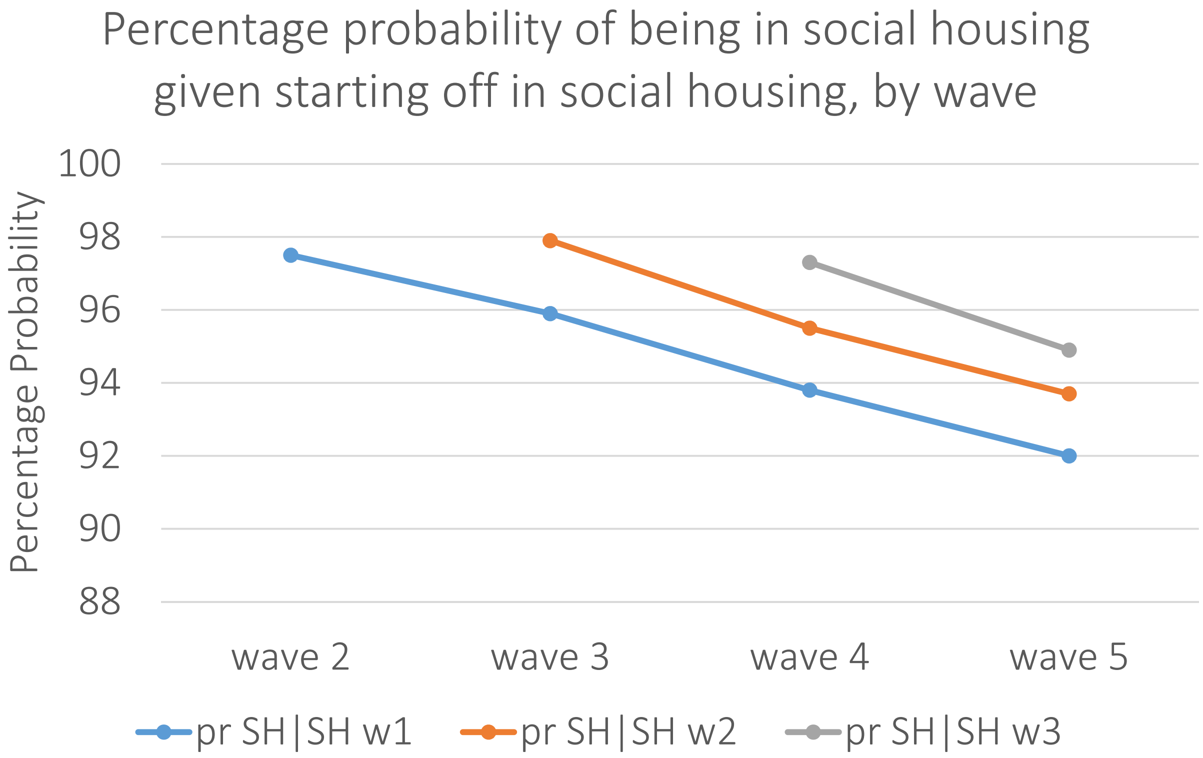
Descriptives – Housing

Previous housing tenure strongly predicts current tenure.

This pattern is repeated across waves.



Descriptives – Employment

Stochastic matrix, employment, w1-w2

Wave 2

Wave 1	Employed	Self employed	unemployed	student	Homemaker	Sick / disabled	retired	other
Employed	86.11	2.77	2.06	0.26	0.81	1	5.28	1.71
Self employed	9.11	75.78	1.98	0.06	0.38	1.15	8.6	2.93
unemployed	35.02	4.67	24.51	1.56	10.89	10.51	7.78	5.06
student	50	7.58	9.09	15.15	9.09	4.55	1.52	3.03
Homemaker	14.04	1.05	11.05	3.16	53.86	5.09	6.84	4.92
Sick / disabled	4.83	0.62	2.88	0.41	2.57	66.8	20.14	1.75
retired	1.11	0.7	0.07	0.02	0.48	1.26	95.6	0.77
other	18.6	7.56	12.21	0.58	11.05	5.23	30.81	13.95

Descriptives – Employment

Stochastic matrix, employment, w1-w2

Probability of moving into unemployed category

		Wave 2							
		Employed	Self employed	unemployed	student	Homemaker	Sick / disabled	retired	other
Wave 1	Employed	86.11	2.77	2.06	0.26	0.81	1	5.28	1.71
	Self employed	9.11	75.78	1.98	0.06	0.38	1.15	8.6	2.93
	unemployed	35.02	4.67	24.51	1.56	10.89	10.51	7.78	5.06
	student	50	7.58	9.09	15.15	9.09	4.55	1.52	3.03
	Homemaker	14.04	1.05	11.05	3.16	53.86	5.09	6.84	4.92
	Sick / disabled	4.83	0.62	2.88	0.41	2.57	66.8	20.14	1.75
	retired	1.11	0.7	0.07	0.02	0.48	1.26	95.6	0.77
	other	18.6	7.56	12.21	0.58	11.05	5.23	30.81	13.95

Descriptives – Employment

Stochastic matrix, employment, w1-w2

More movement than with housing

Wave 2

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Self employed	9.11	75.78	1.98	0.06	0.38	1.15	8.6	2.93
unemployed	35.02	4.67	24.51	1.56	10.89	10.51	7.78	5.06
student	50	7.58	9.09	15.15	9.09	4.55	1.52	3.03
Homemaker	14.04	1.05	11.05	3.16	53.86	5.09	6.84	4.92
Sick / disabled	4.83	0.62	2.88	0.41	2.57	66.8	20.14	1.75
retired	1.11	0.7	0.07	0.02	0.48	1.26	95.6	0.77
other	18.6	7.56	12.21	0.58	11.05	5.23	30.81	13.95

Empirical Strategy

- Panel data model
    - Use repeated observations to remove the impact of fixed individual characteristics (e.g. financial literacy)
    - Use lagged measures of debt to overcome simultaneity
- *Dynamic* panel data model
    - Account for persistence in outcomes using measures from previous periods
- Use a system GMM estimator to account for bias induced by presence of lagged dependent variable in the explanatory variables

Empirical Strategy

Specification: Dynamic Panel Model

$$y_{it} = \alpha + \beta X_{it} + \gamma d_{it-1} + \theta y_{it-1} + c_i + v_{it}$$

y_{it}	is the dependent variable of interest in period t
X_{it}	is a vector of control variables
d_{it-1}	is the explanatory variable, indebtedness, lagged one period
y_{it-1}	is the dependent variable lagged one period
c_i	are the time-invariant characteristics, fixed effects, that we want to control for
v_{it}	is the error term

Empirical Strategy: System GMM

- Control for the lagged dependent variable to capture persistence in outcomes.
- Take first differences to eliminate fixed effects:
  - Problem: The difference in the lagged dependent variable is (typically) endogenous
  - Solution: System GMM estimator uses deeper lags of the dependent variable as synthetic instruments
- System GMM has two nice features:
  - Allow the set of instruments to vary with the observations to maximise sample size
  - Allow the model to be over-identified to maximise efficiency

Results

Housing

- Dependent variable is social housing relative to other housing types
- In the full sample, the coefficient on problem debt lagged one period is 0.002
- As expected from the descriptives, when owners and other small categories are excluded, the coefficient increases to 0.013

Results

Employment

- Dependent variable is whether the respondent is working
- The coefficient on contemporaneous problem debt is -0.001
- The coefficient on problem debt at one lag is 0.011
- Those who are long term sick, retired or in full time education are excluded

Further analysis

Further analysis using the WAS is underway to look at the effect of problem debt on benefit claims

Using other datasets such as the UK Household Longitudinal Study and administrative data from third sector organisations that support people with problem debt, we are also investigating:

- The effect of problem debt on mental health
- The effect of specific debt practices, e.g. use of bailiffs