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Household External Finance and Consumption

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Abstract

This paper uses mortgage data to construct a measure of terms on which households access to external finance, and relates it to consumption at both the aggregate and cohort levels. The Household External Finance (HEF) index is based on the spread paid by risky borrowers in the mortgage market. There is evidence that the terms of access to external finance matter more for the consumption of young cohorts in U.K. data. Results are robust to a wide variety of specifications.

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Keywords: external finance, terms of access, household consumption, birth cohorts, pseudo panels.

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1 Introduction

The impact of credit availability on consumption behavior is a central issue in both theory and practice. The most stylized permanent income model assumes that households can use a combination of saving (internal finance) and borrowing (external finance) with consumption growth being governed by the real interest rate and the subjective time discount factor. A standard caveat to this prediction comes from the possibility that some households may face unfavorable conditions for accessing external finance – either because such finance is rationed or else because the terms are not attractive. However, even though the availability of external finance plays a central role in theoretical thinking about consumption, evidence for its empirical importance remains quite limited.

From a macro-economic point of view, access to credit may play an important role in the monetary transmission mechanism. The conventional financial accelerator model, as discussed in Bernanke and Gertler (1989), and Bernanke, Gertler and Gilchrist (1999), tends to focus on how credit conditions affect the investment decisions of firms. This paper emphasizes similar issues in regard to consumption decisions. This is particularly relevant at present times given the turbulence in financial markets that has been experienced around the globe. A key question is how far these developments will lead to a slow down in consumption growth.

This paper explores the importance of external finance for consumption in the U.K. using a novel measure of the terms available for household external finance. The measure that we use is constructed from mortgage data as the spread over the Bank of England's policy rate paid by risky borrowers. We argue, using a simple model, that this spread should reflect lenders' perceptions of default risk, i.e. the risk/liquidity premium relative to Libor that lenders use to price mortgages, as well as competitive conditions in the mortgage market.

We make two main contributions to the literature on financial constraints and consumption. First, we construct an aggregate index of households' external cost of finance for the U.K. over the period 1975-2005 using mortgage data. Second, we use this index to measure the empirical relevance of financing conditions on consumption growth across household cohorts. Our measure of external financing is based on the spread between borrower-specific mortgage rate and a risk-free rate, and therefore captures the price of borrowing rather than simply the quantity of credit which consumers have access to.

An increase in households' cost of external financing due to a larger spread between the interest rate charged to borrowers and the policy rate, will tend to depress current consumption, because borrowing is less attractive to households.[1] We show that a negative correlation between a tightening in credit conditions and consumption growth is indeed the prediction of a simple model of consumption and secured lending.

Using data from the Family Expenditure Survey (FES), we find a strong empirical link between our Households' External Financing (HEF) index and consumption growth both at the aggregate level and when we disaggregate the data by birth cohort, creating a pseudo panel. The latter exercise reveals that the consumption of the relatively younger cohorts has been the most responsive to our measure of access to external finance.

In Figure 1, the basic pattern that we uncover in the data is illustrated. In particular, we plot our HEF index against aggregate non-housing consumption growth as measured in the U.K. Family Expenditure Survey. Higher values of the HEF measure reflect a larger spread being charged to risky borrowers. The figure suggests a strong, negative correlation between the HEF index and consumption growth of -0.62. We will explore these issues more carefully in what follows.

The next section reviews related theoretical and empirical literature. In section 3, we present a simple model of the credit market and derive our index of households' external costs of finance from the SML dataset. Section 4 shows how we use the HEF index in the micro data on household expenditure. In section 5, we present a simple model of consumption which we then estimate using aggregate and disaggregate data from the FES to assess the impact of the external financing cost index on household expenditure across cohorts. The robustness of the main findings are assessed in section 6 which shows that the results are insensitive to alternative specifications, measures of consumption and level of disaggregation. Section 8 concludes. A description of the data is detailed in the Appendix.

2 Related literature

Our paper is related to the vast prior literature on the determinants of consumption beginning from the classic work of Friedman (1957) and his statement of the permanent income hypothesis. In a seminal paper, Hall (1978) developed the implications of the model for aggregate consumption

[1] One might expect the conditions associated with higher spreads also to be associated with greater credit rationing, which also lowers current consumption compared to the past. Thus the empirical implications for consumption on either interpretation are similar.

using the Euler equation.

The model has been augmented in a variety of directions. Deaton (1991) introduced precautionary savings motive for holding assets and so expanded income to a cash in hand term which covers consumer impatience to model how consumption relates to income given precautionary saving/liquidity constraints. Carroll (1997) also employs a buffer stock version of the permanent income hypothesis.

The implications of liquidity constraints were developed by Zeldes (1989) who emphasizes consumers would be expected to have faster consumption growth between time t and $t+1$ as constraints kept consumption at time t artificially low. Ludvigson (1999) develops a version of the model in which liquidity constraints are binding stochastically.

The link between liquidity constraints and consumption has been the subject of a vast empirical literature that is difficult to condense in a few paragraphs.[2] On macro data, Jappelli and Pagano (1989), Campbell and Mankiw (1989), and Attanasio and Weber (1993) establish the excess sensitivity of consumption to income, which they interpret as indirect evidence for the existence of liquidity constraints.

On international data, Ludvigson (1999), and Bacchetta and Gerlach (1997) provide evidence on the relationship between credit aggregates and aggregate consumption. Calza, Monacelli and Stracca (2007) show that the interest rate elasticity of consumption depends on the structure of a country mortgage market.

The most related contribution to this paper is the work by Aron and Muellbauer (2007). They use an error correction model on aggregate U.K. data from the Office for National Statistics (ONS) to investigate whether the credit conditions index constructed in Fernandez-Corugedo and Muellbauer (2006) affects consumption.

This paper builds on Fernandez-Corugedo and Muellbauer's idea of using data from mortgage lenders to construct a measure of credit conditions. However, we use a rather different procedure to extract our index, which is designed to capture changes in the terms on which external finance is available to households. Another contribution of our paper is to use micro data on households' expenditure aggregated at the birth cohort level to test for heterogeneity in the effects of external financing conditions on consumption.

The idea of using data on cohorts to study consumption was first exploited in Attanasio and Weber (1994 and 1995), and used also in Banks, Blundell and Tanner (1998) and Banks, Blundell and Brugiavini (2001).

[2] See Deaton (1992) and Browning and Lusardi (1996) for an overview.

They report Euler equation estimates for the U.K. and the U.S. which are inconsistent with the permanent income hypothesis.

Using micro data, Hall and Mishkin (1982), Zeldes (1989) and Johnson, Parker and Souleles (2006) for the U.S., and Benito and Mumtaz (2008) for the U.K. develop methods to infer the proportion of liquidity constrained households from expenditure data. Their evidence, however, is indirect since no data from credit market conditions are used in the estimation.

To the best of our knowledge, only few studies have provided direct evidence on the link between consumption and liquidity constraints using micro data. In two event studies, Gross and Souleles (2002), and Agarwal, Liu and Souleles (2007) use credit card data to investigate the impact of credit card limits and the 2001 tax rebates on households' debt. Attanasio, Goldberg and Kyriazidou (2007) use data on car loans to explore the relationship between loan conditions and loan demand. In the study most closely related to our paper, Jappelli, Pischke and Souleles (1999) use the credit index in Jappelli (1990) to estimate a regime-switching Euler equation model on food expenditure. Furthermore, all these studies are for the U.S..

It is worth emphasizing that, unlike previous contributions on micro data, we construct a financing cost index for the whole economy by looking at the lending conditions offered to mortgagors.[3] Furthermore, our index is a time series describing the evolution of the household access to external finance in the U.K. over the last thirty years. This compares favorably to the credit measure in Jappelli (1990) which is drawn from a single cross-section drawn from the 1983 Survey of Consumer Finance.

3 Measuring the cost of external finance

The centerpiece of our analysis is a measure of the terms on which riskier borrowers can access external finance. To motivate the exact measure that we use, we present a simple theoretical model of the pricing of mortgage loans. We then discuss how a regression of household borrowing rates on household characteristics allows us to estimate an index of household external finance access. We then discuss briefly how this relates to our specification of a consumption equation.

[3] According to the 2007 NMG Research survey, mortgagors hold the vast majority of both secured and unsecured debt in the U.K. (see Waldron and Young, 2007).

3.1 Theoretical background

To motivate our measure of the terms on which households gain access to external finance, suppose that a mortgage can be viewed as a series of one period debt contracts and priced relative to a lender's (risk adjusted) opportunity cost of funds denoted by ρ_t. The assumption of a sequence of one period debt arrangements is reasonable for the U.K. market where few borrowers are locked into loan arrangements for significant periods.

Consider a borrower whose probability of repayment is $p(\theta_{it}, z_{it})$ where z_{it} are variables that are observable to the lender, such as being a first time buyer, and θ_{it} are unobserved. Unobserved characteristics include how good a worker the individual is and hence the likelihood that she will become unemployed in future. We suppose, for simplicity, that the latter is a scalar and that $\partial p/\partial\theta_{it} < 0$ so that higher θ_{it} is associated with lower default. The lender will be interested in the distribution of θ_{it} conditional on z_{it} which we denote by $F(\theta|z_{it},\psi_t)$, where $\partial F(\theta|z_{it},\psi_t)/\partial\psi < 0$ it induces a first order stochastically dominating shift in the distribution of θ. For ψ_t, we have in mind observable macro-factors that increase the likelihood of unemployment on the sector in which the individual works. Let

$$\bar{p}(z_{it}, \psi_t) = E\{p(\theta_{it}, z_{it}) : z_{it}, \psi_t\}$$

be the expected default probability conditional on observables. It is easy to see that $\partial\bar{p}(z_{it}, \psi_t)/\partial\psi < 0$.

Suppose that the individual buys a unit of housing of which she borrows a fraction α_i. Thus an individual with lower α_i has higher collateral. Then a competitively determined interest rate for borrower with characteristics (z_{it}) is:

$$\bar{p}(z_{it}, \psi_t)\,\alpha_i\,(1{+}r\,(z_{it}, \psi_t)) + (1\text{-}\bar{p}(z_{it}, \psi_t))\min\{(v_{it} - k)\,,\alpha_i\,[1{+}r\,(z_{it}, \psi_t)]\} {=}\alpha_i\,(1{+}\rho_t)$$

where v_{it} is the expected value of housing owned by individual i at time t per unit of borrowing and k is the foreclosure cost. Solving for the equilibrium interest rate shows that this will vary for two kinds of borrowers depending on their housing collateral. If $v_{it} - k \geq \alpha_i\,[1 + r\,(z_{it}, \psi_t)]$ then

$$r\,(z_{it}, \psi_t) = \rho_t.$$

These individuals are low risk borrowers whose housing collateral is sufficient to repay their loan and cover foreclosure costs in all states of the world. Their loan rate moves with the risk adjusted opportunity cost of funds. Thus, we would expect their borrowing rates to vary with changes in the degree of competition in the mortgage market and/or factors that change either risk or liquidity premia in the market for loanable funds.

If $v_{it} - k_{it} < \alpha_i \left[1 + r\left(z_{it}, \psi_t\right)\right]$, then:

$$r\left(z_{it}, \psi_t\right) = \rho_t + \left[\frac{1 - \bar{p}\left(z_{it}, \psi_t\right)}{\bar{p}\left(z_{it}, \psi_t\right)}\right]\left[1 + \rho_t - \frac{\left(v_{it} - k\right)}{\alpha_i}\right]$$

where the second term on the right hand side includes an additional premium for riskier borrowers. This can be thought of as the households' counterpart of the firms' external finance premium in Bernanke, Gertler and Gilchrist (1999).

The household risk premium will change with the ψ_t factors that affect the subjective risk assessment and with expected house prices. In a world where v_{it} is increasing and/or ψ_t is decreasing, then interest rate premia charged to riskier borrowers will be smaller.

Suppose that

$$\rho_t = \delta_t \left[\rho_t^0 + \rho_t^1\right]$$

where ρ_t^0 is Bank Rate and ρ_t^1 is an unobserved risk/liquidity premium and δ_t is a mark-up reflecting competition in the credit market. Then the spread between the borrowing rate faced by each household and the Bank rate, $r\left(z_{it}, \psi_t\right) - \rho_t^0$, is given by:

$$\begin{cases} (\delta_t\text{-}1)\rho_t^0 + \delta_t\rho_t^1 & \text{if } v_{it}\text{-}k \geq \alpha_i \left(1 + (\delta_t\text{-}1)\rho_t^0 + \delta_t\rho_t^1\right) \\ (\delta_t\text{-}1)\rho_t^0 + \delta_t\rho_t^1 + \left(\frac{1\text{-}\bar{p}(z_{it},\psi_t)}{\bar{p}(z_{it},\psi_t)}\right)\left[1 + \rho_t\text{-}\frac{(v_{it}\text{-}k)}{\alpha_i}\right] & \text{otherwise} \end{cases} \tag{1}$$

This set up is similar in spirit to Jeske and Krueger (2005), who study the welfare implications of implicit government guarantees on aggregate credit risks.

This model motivates why low collateral borrowers (higher α_i) will pay a higher risk premium. We also expect borrowers with riskier observable characteristics z_{it}, such as being a first buyer, to pay a higher risk premium.

Suppose that we can observe in the data $\left(z_{it} \text{ and } \rho_t^0\right)$, then the expressions in (1) show that we should be able to extract information about changes over time in δ_t and ρ_t^1 from all borrowers. However, for the riskiest borrowers we can extract information about the house price expectations and subjective estimate of ψ_t by looking at the spreads they paid. This is the empirical procedure that we follow.[4]

[4] In fact, α_t and ρ_t^1 affect the classification of a borrower as risky in our terms, and the dependence of the spread on these variables is different for riskier borrowers. This is

3.2 Empirical implementation

In this section, we present the construction of our index of households' external financing costs based upon the SML dataset, whose full description is given in the Appendix. An average of $40,000$ randomly selected borrowers has been surveyed each year over the period 1975-2005. The number of interviewees ranges from $35,000$ in 1975 to $115,000$ in 2005.

Our goal is to create a measure which captures the terms on which riskier households can gain access to credit. To this end, we use information on housing tenure status and collateral values to identify the borrowers who may be viewed as 'risky' by the lenders. More specifically, we focus on First Time Buyers (FTB) who have been able to pay down only a small initial deposit. To make individual collateral values comparable across time, we normalize them using regional house price. A preliminary exploration of the data reveals that the relationship between individual interest rate spreads and the logarithm of real collateral as a kink around the value of 2 for real collateral. Accordingly, we classify in the low collateral group all borrowers with a real initial deposit below this value.[5]

For each year in our panel, we run a regression for the interest rate spread, $x_{i,t}$, paid by each borrower in the low collateral group on individual characteristics and macroeconomic conditions. The spread is measured as the difference between the rate individuals are charged on new mortgage lending and the 3 month Treasury Bill rate in the month that the lending occurred. The regression takes the following form:

$$x_{i,t} = \mu_{r,t} + \mu_{FTB,t} + \gamma z_{i,t} + \varphi \Delta q_{r,t} + \varepsilon_{i,t} \tag{2}$$

where $\mu_{r,t}$ is a vector of (Standard Statistical) region dummy variables in year t, $\mu_{FTB,t}$ is a dummy variable indicating if the individual is a first-time buyer, z_i includes income, y_i, age, loan size, the value of the house, v_i, the value of collateral, age interacted with loan value for the individual i, and $\Delta q_{r,t}$ is regional real house price inflation. All variables except interest rates are in logarithm.

As we argued above, there are good reasons to believe that borrowers in observably higher risk groups would be charged at a higher rate, condi-

consistent with the observation on U.K. data that the spread of mortgage rates over the Bank rate varies with the collateral position of each household (see Aoki, Proudman and Vlieghe 2004).

[5] As we transform the data by taking logarithms, borrowers in the zero collateral group, who represent on average 4.8% of the entire population, are excluded from our estimation. The cut off point of 2 corresponds to about 3% of the loan to value ratio for the average house price in 2005.

tional upon the observable characteristics $z_{i,t}$. The coefficient on the FTB dummy, $\mu_{FTB,t}$, in equation (2) for the low collateral group is meant to capture the premium that riskier borrowers with no credit history are asked to pay. Then, our Household External Finance (HEF) index is constructed by combining into a time series the estimated coefficients on $\mu_{FTB,t}$ for each year t.

In Figure 2, we plot the HEF index against annual FES consumption growth for six birth-cohorts. High values of the HEF index represent an increase in the households' cost of external financing. We note that the contemporaneous correlations between cohort consumption and the HEF index is always negative with a peak for the households in the cohorts covering 1946-55.[6] As our panel is stratified by the level of real collateral as opposed to birth groups, the HEF index does not vary across birth cohorts.

In Figure 3, we show the width of the 95% confidence interval for the HEF measure: variation in pricing responses to first time buyers' deals within the low collateral group has significantly declined over time. It is worth emphasizing that the time profiles of both the HEF index in Figure 1 and the standard errors associated with its point estimates in Figure 3 are consistent with the significant waves of financial liberalization of the 1980s, namely the entry of commercial banks into the mortgage market (previously played only by building societies) and the introduction of securitization products. Since the mid-90s, the volatility of both series has declined.

4 Consumption growth and external finance

This section discusses how we use the HEF index to study consumption and how this links back to underlying theories of consumption behavior based on the life-cycle permanent income model.

We expect the measure of external financial conditions that we have extracted from mortgage data to be reflecting how credit markets are pricing risk to riskier classes of borrowers. The theoretical relevance of this to estimating consumption is not immediately clear but can be motivated using the classical Euler equation for inter-temporal consumption employed in most modern empirical work on consumption.

[6] In particular, the correlations are: -0.20 (1941-45), -0.58 (46-50), -0.47 (51-55), -0.22 (56-60), -0.01(61-65), -0.42 (66-70).

4.1 Theoretical background

Consider an infinite horizon economy where each household i chooses the plan for consumption, $C_{i,t}$, and assets, $B_{i,t}$, that maximizes the utility function $u\left(C_{i,t};\gamma_{i,t}\right)$, where $\gamma_{i,t}$ and are household-specific characteristics. The optimal plan is subject to the following constraints:

$$\begin{aligned} C_{i,t}+Q_t\left(H_{i,t}-H_{i,t-1}\right) &\leq Y_{i,t}+B_{i,t-1}\left(1+r_t\right)-B_{i,t} \quad \forall\ t\text{=}1..T & (3)\\ B_{i,t} &\geq -\bar{\alpha}_i E\left(Q_{t+1}\right)H_{i,t} \quad \forall\ t\text{=}1..T\text{-}1 & (4)\\ B_{i,T} &\geq 0 & (5)\end{aligned}$$

where Q_t is the real price of a unit of housing $H_{i,t}$, real income is denoted by $Y_{i,t}$, the real interest rate is r_t, the expectations operator is $E\left(\cdot\right)$ and $\bar{\alpha}_i$ represents the multiplier on the expected value of a unit of housing which establishes the maximum amount of secured lending that each household i can raise at time t. Note that in the UK mortgage market the multiplier $\bar{\alpha}_i$ is determined in terms of the loan rather than the repayment.

The expression in (3) is the household-specific budget constraint whereas (4) and (5) are the household-specific borrowing constraint and no Ponzi condition.[7]

Due to unmodelled credit market imperfections, the economy is populated by two types of households, *constrained* and *unconstrained*, which are of measure λ and 1-λ, respectively. The unconstrained households are offered an interest rate r_t^L at which they can either lend or (safely) borrow. The second type of households face a binding borrowing constraint (4) and they are charged an interest rate $r_t^B > r_t^L$, which reflects the fact that they are viewed as 'riskier' by the lenders.[8]

Denoting by β_i the (possibly heterogenous) discount factor, the first order conditions for the household's asset position are then:

$$u_c\left(C_{i,t};\gamma_{i,t}\right)=\beta_i E\left\{u_c\left(C_{i,t+1};\gamma_{i,t+1}\right)\left(1+r_{t+1}^L\right)\right\} \tag{6}$$

for the unconstrained households, and:

$$u_c\left(C_{i,t};\gamma_{i,t}\right)Q_t(1-\bar{\alpha}_i\frac{Q_{t+1}}{Q_t})\text{=}\beta_i E\left\{u_c\left(C_{i,t+1};\gamma_{i,t+1}\right)Q_{t+1}\left[1\text{-}\bar{\alpha}_i\left(1\text{+}r_{i,t+1}^B\right)\right]\right\} \tag{7}$$

[7] See Zeldes (1989), Flemming (1973) and King (1986) for the case of unsecured lending.

[8] Nominal contracts, as in Iacoviello (2005), and housing depreciation, as in Calza, Monacelli and Stracca (2007), are not central to our analysis and would complicate the algebra without altering the message of this section.

for the constrained borrowers.

To move towards an aggregate consumption equation, we take logs of both sides of (6) and (7). For consistency with the empirical analysis of Section 3, where we have normalized individual borrowing rates by the Bank of England policy rate, we rewrite the log-linearized version of (7) in terms of the spread between borrowing and lending rates.[9] Assuming an utility function of the form $[C_{i,t}^{1-\sigma}/(1\text{-}\sigma)\exp(\tau\gamma_{i,t})]$, we obtain the following consumption function for the whole economy:

$$\Delta c_{t+1} = \frac{1}{\sigma}\left\{ \begin{array}{c} \ln(\beta) + \tau\Delta\gamma_{t+1} + \lambda(1+\bar{a}_i)\Delta q_{t+1} + \\ +[1-\lambda(1+\bar{a}_i)]\, r_{t+1}^L - \bar{\alpha}_i\lambda\left(r_{t+1}^B - r_{t+1}^L\right) + \varepsilon_{t+1} \end{array} \right\} \tag{8}$$

where a variable x_t denotes $ln(X_t)$, Δ is the first difference operator and ε_{t+1} is a combination of expectation and approximation errors. Were no borrower constrained, ie $\lambda = 0$, equation (8) would reduce to the standard Euler equation. In the special case of $H_{i,t} = 0$, we obtain a positive relationship between consumption growth and the shadow price associated with the borrowing constraint (see Zeldes, 1989).

It should be noted that all variables in (8) are averages over the relevant populations. According to our consumption model, the term $\left(r_{t+1}^B - r_{t+1}^L\right)$ is the average spread over the cohort of constrained borrowers (net of the components attributable to individual characteristics), and it is therefore consistent with the HEF index developed in Section 3.

4.2 Empirical implementation

In light of the theoretical considerations above, we will aggregate micro data to estimate the following reduced-form consumption growth equation at the aggregate level:

$$\Delta c_t = \theta_0 + \theta_1 r_t + \theta_2\Delta y_t + \theta_3 HEF_t + \theta_4\Delta q_t + \theta_5\Delta\gamma_t + \eta_t \tag{9}$$

where r_t is a risk-free rate and Δy_t is real income growth, as suggested by the empirical literature on excess sensitivity.

[9] The formulation in terms of a spread measure is consistent with the idea that households can use flexible mortgage borrowing arrangements to manage their inter-temporal consumption decision rather than the Treasury Bill rate, which is more likely to be relevant for saving. Obviously, this ignores the fact that unsecured credit (particularly credit card borrowing) is also used for consumption smoothing. To extent that the factors driving risk premia in mortgage lending are correlated with the determinants of risk premia in the credit market as a whole, however, we would expect HEF also to measure some aspects of access to all credit. We return on this issue in Section 6.1.

Several authors including Campbell and Cocco (2007), Attanasio et al. (2005) and Benito et al. (2006) have explored the empirical correlation between real house price inflation and consumption growth. A possible interpretation is that house price inflation may be a better proxy for expected future income than current income growth. An alternative view is that such a link may represent a wealth effect. While identifying these two channels would probably require the estimation of a fully specified general equilibrium model, we note that the structural equation (8) is only one of several alternative mechanisms which may generate a reduced-form specification such as (9). This should bear in mind in the interpretation of our results.

The vector γ_t includes age, age squared, family size and family size squared. As measurement errors in differentiated data and time aggregation may introduce MA components in the error term, standard errors are adjusted for serial correlation up to order three as well as heteroskedasticity.

We are particularly interested in whether θ_3 has any explanatory power in such an equation. If HEF_t is picking up the extent of credit access for households, we would expect it to enter (9) with a negative sign reflecting the fact that (the presence or the anticipation of) more cautious lending, as implied by a higher spread, reduces current consumption.

The FES covers a randomly selected sample of around 7000 British households per year. The full dataset consists of a time-series of repeated cross-sections, and therefore the method introduced by Deaton (1985) can be used to create a pseudo-panel. For each variable and year, we take geometric means and compute: *(i)* a single time-series on average data, including most households in the survey; *(ii)* six time-series on average cohort data, including only the participant households whose head was born in the intervals 1941-45, 46-50, 51-55, 56-60, 61-65, 66-70.[10]

At this disaggregated level, the core equation to be estimated is:

$$\Delta c_{b,t} = \kappa_b + \kappa_1 r_t + \kappa_2 \Delta y_{b,t} + \kappa_3 HEF_t + \kappa_4 \Delta q_t + \kappa_5 \Delta \gamma_{b,t} + \eta_{bt} \qquad (10)$$

where a subscript b refers to a birth cohort and where κ_b is a vector of birth cohort dummies. To look for heterogeneity in the impact of the HEF measure we will augment (10) with a set of interaction terms between HEF_t and birth cohort. This will allows us to see how far different cohorts have responded to changes in the terms on which external finance is available.

[10] We consider only cells with at least 120 observations per year. The birth bands were chosen so as to maximize the number of time-series observations available for each cohort.

5 Evidence from aggregate FES data

In this section, we present results based on the merge between synthetic annual data on households' external financing costs from the SML and synthetic annual data on household expenditure from the FES. The description of the data sets is provided in the Appendix.

5.1 Main results

Our baseline measure of consumption is non-housing expenditure and services. The explanatory variables include the 3 month Treasury bill rate, demographic variables, disposable income, national house prices and the HEF index whose construction we discussed in the previous section. We deflate the relevant variables using the Retail Prices Index excluding mortgage interest payments (RPIX), normalize consumption and income by family size, and then take first differences of all variables except the interest rate and our credit index. To make the coefficients on r_t and HEF_t of comparable orders of magnitude, prior to estimation we standardize the credit index and scale it up by the standard deviation of the Treasury Bill. The sample covers the years between 1975 and 2005.

Our goal is to investigate the link between consumption and HEF in the aggregate. For each year, then, we compute the average expenditure value across most participating households in the FES.[11] In Table 1, we report the OLS results. In the first column, we show the estimates of a baseline specification in which consumption displays the usual "excess sensitivity" to income. The results reported here are not statistically different from the estimates reported in Attanasio and Weber (1993). In the second column, we add our measure of households' external cost of financing, which is found to have a significant negative coefficient.

To give an order of magnitude for the aggregate effect predicted by the estimates in Table 1, we note that a one standard deviation increase in the HEF index is associated with a fall in annual consumption growth a little below 1%. This is the same as saying a 100 basis points increase in the wedge between borrowing and lending rates is associated with a fall in annual consumption growth a little below 0.29%.

The inclusion of house price inflation in the specification in the third

[11] For consistency with the cohort analysis below, we report aggregate estimates based on (i) all households whose head is born between 1940 and 1970, and (ii) cells with a minimum of 120 observations.

column improves the fit further.[12] The estimated coefficient on Δq_t is significant but smaller than the value found by Campbell and Cocco (2007) whose analysis is based on quarterly data and a shorter sample. The results imply that a 1% change in house prices is associated with a 0.17% change in consumption growth.

The most general specification in the last column is associated with a R^2 of 0.71. The coefficient on the real interest rate is robust across models but the coefficient on income growth becomes only marginally significant at the 10% level. Consumption growth is a positive function of age, though at a decreasing rate, and the rate of house price inflation remains significant. The HEF index confirms itself as a significant driver of consumption.

The inference based on OLS relies implicitly on three assumptions. First, current values of the real interest rate, real income growth and real consumption growth are good proxies for their expected values. Second, measurement errors are averaged out by aggregating over households. Third, the explanatory variables, including inflation expectations and the nominal interest rate, are exogenous to consumption growth.

One way to assess the extent to which these assumptions affect our findings is to estimate the consumption function using instrumental variables, with lagged values of consumption growth, income growth, inflation and the nominal interest rate as instruments for their current values. In selecting the lag lengths of the instruments, it is important to bear in mind two issues which may introduce an MA(1) component in the error term. First, the data are at annual frequency and hence are time averaged.[13] Second, the disturbance embodies an expectation error. The first order serial correlation in the error term implies that the first lag of the instruments would lead to inconsistent estimates, as argued by Bean (1986). We therefore use the second and third lags of consumption, income, inflation and the nominal interest rate as additional instruments. We also add the lag of house price inflation and the HEF index to the instrument list in an effort to capture expectations of future house prices.[14]

In Table 2, we report the estimates of the aggregate consumption equation obtained with the Generalized Method of Moments (GMM) using an

[12] As argued in the previous section, this could either be interpreted as a wealth effect working through imperfections in the credit market or as a proxy for permanent income.

[13] When the households' decision period is shorter than the data sampling interval, Christiano, Eichenbaum and Marshall (1991) show that the time-average of multiple decisions introduces a spurios first order serial correlation in consumption growth.

[14] The use of the first lag of HEF as instrument also accounts for the fact that the HEF index is a generated regressor (see Pagan, 1984, and Pagan and Ullah, 1988).

optimal weighting matrix that accounts for the possibility of heteroskedasticity and serial correlation in the error terms (see Hansen, 1982). In practice, we employ a three lag Newey-West estimate of the covariance matrix.

The GMM estimates confirm, by and large, the results based on the OLS. The large negative coefficient on the HEF index is always significant, while income growth loses its explanatory power in the most general specifications on the right of Table 2. Age has a nonlinear effect on consumption and house price inflation has a small but significant positive correlation with consumption growth.

5.2 Sensitivity analysis

As a way to assess the robustness of our findings, we estimate the consumption equation using the aggregate data released by the ONS, and the aggregate data on non-durables expenditure constructed from the FES.

ONS consumption data

An alternative way to account for the measurement errors in the micro data is to employ contemporaneous values of (seasonally adjusted) consumption growth and income growth from the Office for National Statistics (ONS) as instruments for their FES counterparts, while keeping the second and third lags of inflation and the Treasury Bill rate as instruments for the real interest rate.

These results are reported in Table 3, and they are a useful check for the sensitivity of our results to using a smaller instrument set. The estimates in the first four columns are not statistically different from the values reported in Table 2, and thus they confirm the empirical relevance of the household terms of access to the credit market for consumption.

Earlier contributions have found little support for the real interest rate in a consumption growth equation estimated using aggregate data from national statistics as regressand (see for instance Campbell and Mankiw, 1990). In Table 4, we use ONS non-housing consumption as our dependent variable. The estimates for the baseline specification in column 1 confirms Campbell and Mankiw's findings on excess sensitivity. When we include our HEF measure in column 2, however, income growth loses significance, and adding house price inflation in the last two columns makes the coefficient on the real interest rate statistically different from zero.

Non-durable consumption

In Table 5, we use non-durable consumption and services rather than non-housing expenditure and services as the dependent variable. The results confirm our previous findings that the coefficient on our HEF measure is negative, large, and significant, while income growth loses its explanatory power in the most general of specifications.

6 Evidence from disaggregated data

The evidence on aggregate FES data corroborates the idea that the costs of external financing is significantly correlated to consumption growth. In this section, we assess the extent to which the aggregate results are robust to splitting the FES sample according to birth cohorts. In so doing, we will also be able to explore the importance of heterogeneity in responses to changing household financing conditions across cohorts.

6.1 Main results by birth cohort

The results in Table 6 present evidence using OLS while including a cohort fixed effect and a separate linear time trend for each birth cohort. Standard errors are adjusted for intra-group correlation.

The coefficients in the first column are similar to those obtained in Attanasio and Weber (1993). Using a shorter time period, Banks, Blundell and Tanner (1998), and Banks, Blundell and Brugiavini (2001) also obtain estimates of the consumption sensitivity to the real interest rate which are not statistically different from ours.

The impact of the external financing cost on consumption is negative, large and significant in columns 2 and 4. When we interact the HEF index with birth cohort specific dummy variables in column 5, we find evidence in favor of heterogeneity. In particular, the effect of our HEF measure on the consumption growth of the oldest cohort is insignificantly different from zero, while the effect is significant for all other cohorts. The youngest cohort, with a household head born between 1966 and 1970, is associated with the "peak effect" of the HEF index, which is significantly larger than for any other cohort.

The real interest rate and income growth both have explanatory power, with point estimates robust across specifications. House price inflation is also significant at a 5% level.

As for the GMM, we report results based on the two instrument sets discussed above. For all estimates, the null hypothesis of weak instruments is rejected on the basis of the Anderson's canonical correlation statistics while the null hypothesis of valid overidentifying restrictions is not rejected on the basis of the Hansen's J statistics.[15] All specifications include a dummy and a linear time trend for each birth cohort. Standard errors are computed using a three lag Newey-West adjustment.

Our finding of heterogeneous responses to the HEF index is robust to using GMM, as shown in Table 7. The standard errors are larger than in the OLS case, possibly reflecting the fact that the numbers of cohorts and instruments imply there are insufficient degrees of freedom to use an optimal weighting matrix which is robust to intra-cluster correlation.

The point estimates of the coefficient on the real interest rate is systematically higher than in Table 6, suggesting that the OLS results may suffer from measurement errors and endogeneity. In contrast to the OLS estimates, the parameter on income growth in Table 7 is not statistically different from zero when real house price inflation is included in column 3, and in the more general specifications reported in columns 4 and 5. The attenuation and loss of significance of the income growth coefficient in columns 3, 4 and 5 is consistent with the idea that income growth, in the baseline model of column 1, may be capturing income expectations as well as the existence (or the expectation) of unfavourable terms on which external finance can be accessed by households.

Interpreting the results

The HEF index is based on the premia paid in the mortgage market by first time buyers in the low collateral group. While this class of borrowers typically does not count for more than 8% of the mortgage deals in a given year, it may allow us to identify a measure of access to credit for a far wider group of households facing similar borrowing conditions. In terms of the model in section 3.1, this would be true to the extent that our measure is partly picking up factors that are included in ψ_t which reflects common underlying factors (such as the risk of unemployment in particular groups) that have implications for a wider class of borrowers.

Earlier studies of the effect of credit constraints, such as Zeldes (1989) have proceeded by classifying consumers into constrained and unconstrained on a priori basis rather than having a direct measure of credit market conditions. If our HEF measure is indeed a good proxy for the credit conditions affecting a wider group, it seems reasonable that these will have a greater impact on the younger consumers within a cohort. Indeed, since most first time buyers are young and have little opportunity to acquire collateral, this is what our HEF measure reflects. This line of reasoning suggests that, for

[15] The results of the tests are not reported but available from the authors upon request.

the groups that are significantly affected by credit conditions, the impact of the HEF index should be similar in magnitude to the extent of consumption excess sensitivity to income.

We investigate this issue by running a regression in the spirit of Campbell and Mankiw (1989). In particular, we estimate on the micro data a standard consumption growth equation, without the HEF index, but augmented with slope heterogeneity in the excess sensitivity to income growth across birth cohorts. To the extent that our measure captures aggregate credit conditions, we would expect the change in consumption growth implied by a one standard deviation movement in income growth to be of a similar magnitude of the change in consumption growth implied by a one standard deviation movement in credit conditions.

The estimates of this exercise are reported in column 6 of Table 7 and they suggest two conclusions. First, in line with the results on the HEF measure, the consumption of the youngest cohort is the most sensitive to fluctuations in income growth. The coefficients on Δy_t for the oldest cohorts, in contrast, are not statistically different from zero. Second, a one standard deviation fall in income growth for the youngest group implies a decline in aggregate consumption growth of 1.1%, based on their share of expenditure in 2005. This number is remarkably similar to the 1% obtained using HEF.

While not conclusive, this evidence does suggest that in quantitative terms, at least, the size of our estimated effect is consistent with the HEF index picking up a wider measure of access to credit among the young. Since mortgage credit to inexperienced borrowers with no collateral is the closest (among secured credit) to unsecured credit, it seems a reasonable conjecture that this could well be a proxy for unsecured credit conditions. However, until we are able to conduct a similar exercise on contracts for unsecured credit, this claim is somewhat speculative.

6.2 Sensitivity analysis

In this section, we assess the sensitivity of our results on micro data to three modifications of our estimation strategy. First, we use ONS consumption data as instruments. Second, we consider a further level of disaggregation by age. Third, we employ non-durables expenditure as dependent variable. The finding that the consumption of young households is more influenced by credit conditions relative to the consumption of older households is shown to be robust to each of these modifications.

In further sensitivity analyses, not reported but available upon request, we also find that (i) deflating all variables with a divisia price index rather than RPIX,[16] and (ii) using the time deposit rate rather than the 3 month Treasury bill rate do not affect our main conclusions on the importance of access to external finance in affecting consumption growth.

ONS consumption data

In Table 8, we note that using a smaller instrument set produces estimates very similar to those in Table 7. The coefficient on the HEF index is highly significant in the more aggregate specifications in columns 2 and 4, and is significant only for a younger cohort reported in the heterogenous cohort specification in column 5.

Age and birth cohorts

In interpreting the results above, we rely on the notion that the birth cohorts provide a reasonable approximation for the age cohorts. The cohort in which the head of household is born between 1940 and 1945, for instance, can be thought as the oldest consumers in our sample while the cohort in which the head of household is born between 1965 and 1970 can be thought as the youngest consumers.

We can further divide our sample by using information about age. The idea is that the consumption of a family whose head was born in 1942 and interviewed in, say, 1975 may be different from the consumption of a family whose head was born in 1942 but was interviewed in 2005. Data availability, however, limit the level of disaggregation. The FES is based on 7000 household interviews per year, and with the birth cohorts spanning the 1950s or the 1960s our constraint of 120 observations per cell becomes binding fastly when splitting cells by age.

In an effort to maximize the number of households per cell and the number of time-series observations per cohort, we label as 'young' ('old') the households whose head is aged below or equal to (above) 35 at the time of the FES interview. This age threshold allows us to split further the birth cohorts between 1951 and 1960.

As for the birth cohorts between 1940 and 1950, there are insufficient observations to generate sufficiently large 'young consumers' sub-groups. And similarly, for the birth cohorts between 1961 and 1970, there are insufficient observations to generate 'old consumers' sub-groups. Hence, for these cohorts, we do not try any further level of disaggregation.

[16] For each household, the divisia price index is constructed as the average of the price indices of the categories of goods and services in the reported expenditure, weighted by the household-budget shares.

The results on the age and birth cohorts are reported in Table 9 and confirm the significant heterogeneity in the effect of households' external cost of financing across groups. The consumption of the household whose head is born between 1941 and 1945 are not affected by the HEF index. Moving to the two birth cohorts between 1951 and 1960, we find that the impact of our measure of access to external finance is significant for the expenditure of the young households, but is not statistically different from zero for the older households in the same birth group.

The coefficients on the HEF index in the birth cohorts 1961 to 1965 and 1966 to 1970 are also negative and significant, as we may expect given that these groups are dominated by the young throughout our sample. The last birth cohort is also associated with impacts of financing costs which are significantly larger than the impacts on other cohorts. In summary, we find further evidence in support of the notion that the young are more exposed to changes in the terms on which they access the credit market than the old.

Non-durable consumption

Finally, we investigate the robustness of our results to using non-durable consumption and services rather than non-housing expenditure and services as dependent variable. The results are reported in Table 10. The significance and heterogeneity of the HEF index across cohorts are largely unaffected by the change in the left-hand side variable, although the interaction between HEF and the 1956 to 1960 birth cohort does lose significance.

According to our estimates, the youngest cohort is the group of households whose consumption is most exposed to changes in the terms of access to finance. For this last cohort, a one standard deviation tightening in credit conditions is associated, on average, with a fall in annual consumption growth of around 1.85%. This is equivalent to say that a 100 basis point increase in the interest rate spread paid by the riskiest borrowers is associated with a fall of 0.56% in their consumption growth. In columns 4 and 5, the coefficients on house price inflation are significant but smaller in magnitude than when non-housing expenditure and services were used as the dependent variable in Table 6.

7 Conclusions

This paper has investigated the link between consumption and the terms of access to external finance by households measured from interest rate spreads on mortgages. We have shown that the HEF index that we construct from mortgage data is robustly correlated with consumption growth between 1975 and 2005, with stronger effects in younger birth cohorts. These findings are robust to a wide variety of empirical specifications.

Taken together, the results support the claim that the terms on which households can access to external finance to smooth their consumption matter for consumption growth. The improved terms on which households can access credit can, according to our measure, account for a significant amount of the growth in consumption over the period of our study. An increase of 100 basis points in the wedge between borrowing and lending rates is associated, on average, to a fall in aggregate annual consumption growth of about 0.3%. As in the past thirty years or so non-negative individual interest rate spreads in the UK have averaged around 160 basis points, with peaks above 1000 basis points, the impact of credit conditions on consumption growth is certainly of economic significance.

In a broader macro-economic context, our results complement existing work on the financial accelerator through changing access to credit for businesses as in Bernanke, Gertler and Gilchrist (1999). The literature to date has emphasized the link to business investment from changing credit conditions. The results reported here suggest that there is scope for a quantitatively significant direct channel from credit conditions onto household behavior through the way in which risk is priced in the markets for secured household debt.

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Data Appendix

This Appendix provides further details on the SML and FES data sets used for the estimation in the main text.

Survey of Mortgage Lenders

In order to construct our HEF index measure, we use mortgage origination data covering the period 1975 to 2005 from the Survey of Mortgage Lenders (SML) and its predecessor, the 5% Sample Survey of Building Society Mortgages (SBSM). These surveys are available in electronic format for the years 1975 to 2001 from the Data Archive at the University of Essex. Unfortunately, the year 1978 is missing, and so we have interpolated the 1978 data where relevant. Data covering the period 2002 to 2005 was obtained by the Bank of England from the Council of Mortgage Lenders (CML).

The switch between the SBSM and SML surveys reflected the changing nature of the mortgage market in the U.K.. Increased competition from Banks and other specialist lenders combined with the demutualisation of the Abbey National resulted in the creation of the CML in 1989, and eventual extension of the SBSM to accommodate all members of the CML in 1992. In 2003 the SML sample size was expanded, with most contributors providing a full sample of mortgage completions rather than a 5% random sample.

The surveys provide a range of information including data covering characteristics of the loan at origination (the loan size, purchase price, gross rate of interest, whether the interest charged is fixed or variable, repayment method, etc.) and individual borrower characteristics (sex and age of borrowers, income on which the mortgage is based, previous tenure, region etc). The surveys form a repeated cross-section and the method in Deaton (1985) can be used to construct a pseudo-panel.

To obtain estimates for our measure of the HEF index we supplement data from the SBSM/SML on loan size, property value, gross interest rate, age and income, with regional house price data from the Nationwide house price index. We also place the following restrictions upon the data and:

1. discard individuals over the age of 75 and under 21.

2. omit individuals buying a house with a price discount and who were previously local authority or housing association tenants.

3. exclude sitting tenants not-covered by restriction 2.

4. discard observations where lending is not for house purchase (further advances and remortgaging activity).
5. omit observations for individuals with outlying loan-to-income (LTI) and loan-to-value (LTV) ratios. The threshold levels chosen were LTI>=10, and LTV<0.2 or LTV>1.1.
6. discard observations with a gross interest rate below 0.5% per annum, or where the absolute value of the spread between the gross rate of interest and the 3 month Treasury Bill rate is greater than 10% of the Treasury Bill rate.
7. omit observations where relevant data are missing.

In Table 11, we provide descriptive statistics of the SML data we use.

Family Expenditure Survey

We use data on household consumption, disposable income, demographics and housing status from the Family Expenditure Survey available online at http://www.data-archive.ac.uk/findingdata/festitles.asp. The sample spans the period 1975-2005, with the first observation associated with the beginning of our SML data set and the last observation marking the latest available data in July 2007 when the data were collected.

Our baseline measure of consumption is non-housing expenditure and services, defined as total expenditure minus expenditure for housing plus 'repair' and 'do it yourself' (diy). Non-durable consumption is the sum of two week reported expenditure on food, catering, alcohol, tobacco, fuel, household services, clothing, personal goods and services, fares, leisure services, consumables, pet care, repair, diy, motoring expenditure, recreational goods.

Nominal variables are deflated using the Retail Prices Index minus mortgage interest payments (RPIX). Consumption and income are divided by the size of the household, $fsize$. The variable *age* refers to the age of the head of household, defined on the basis of income. The variable *owner* stands for the proportion of homeowners in each cohort.

To ensure the FES data are representative of the UK population, we plot in Figure 4 the aggregate per-capita non-housing real consumption growth from the FES and the corresponding ONS series. For the sake of comparability with the ONS data, in Figure 4, and only in Figure 4, the FES consumption growth is computed as the log difference of the average of all households in the FES panel, i.e. arithmetic mean.

In Tables 12 and 13, we report descriptive statistics for our FES dataset.

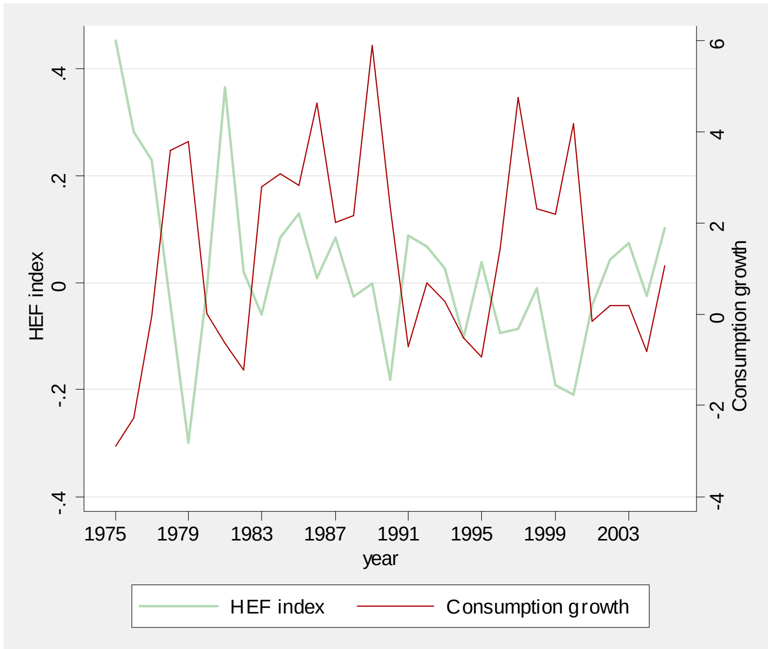

Figure 1: Aggregate FES consumption growth and HEF index

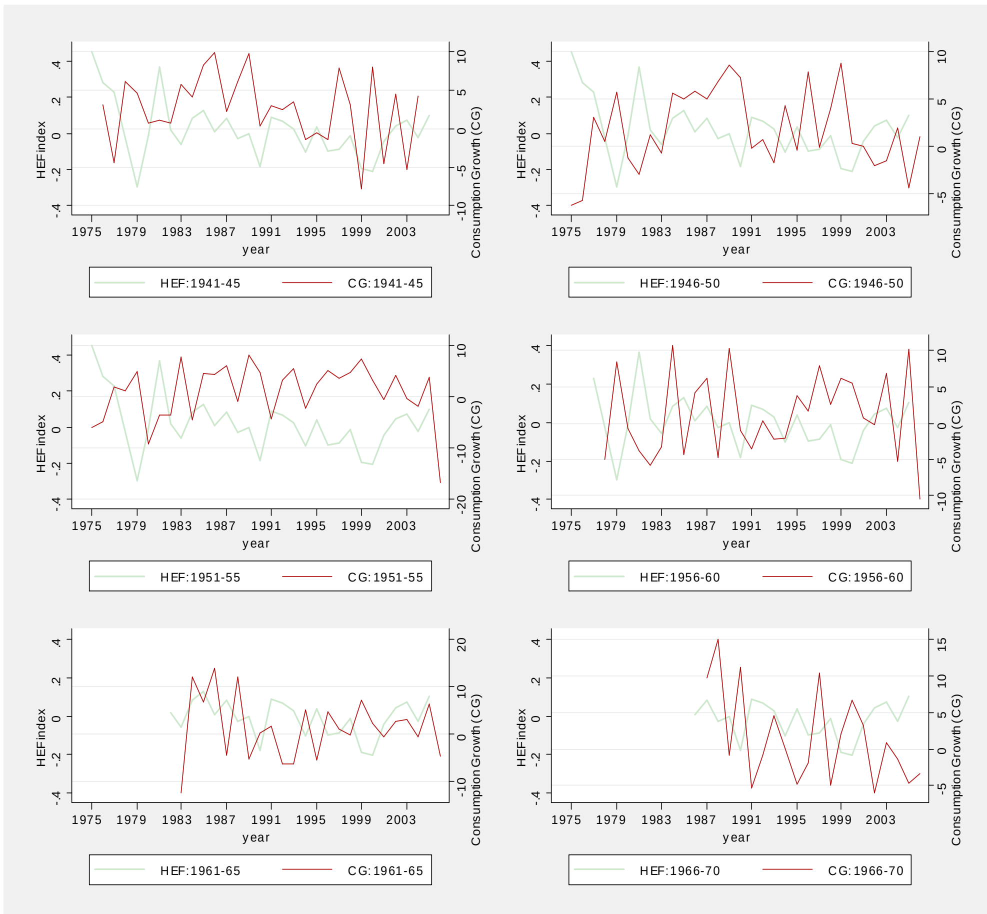

Figure 2: FES consumption growth and HEF index by birth cohort

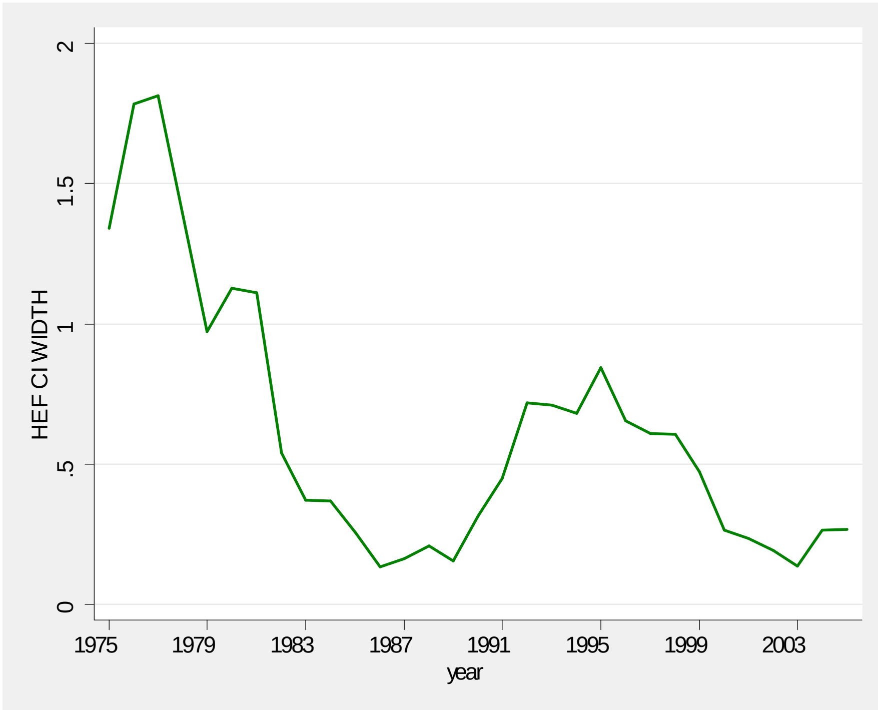

Figure 3: HEF Confidence Interval Width

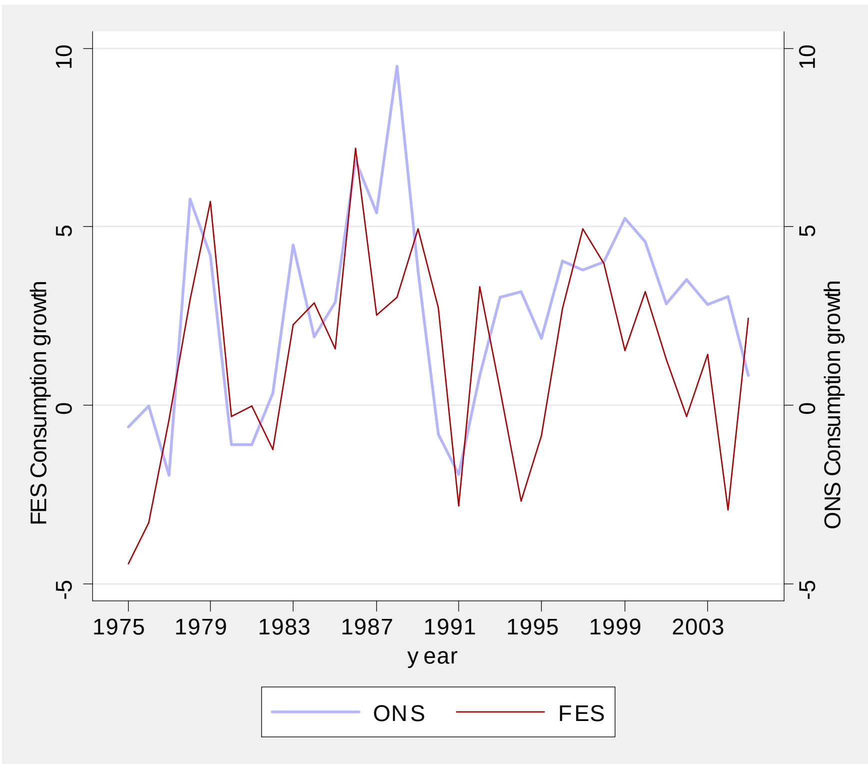

Figure 4: FES and ONS consumption growth, arithmetic averages

Table 1: Aggregate FES consumption, OLS

	(1)	(2)	(3)	(4)
	baseline	*HEF*	*hp*	*HEF & hp*
coefficient				
r_t	0.312***	0.187**	0.272***	0.167**
	(0.069)	(0.087)	(0.065)	(0.074)
Δy_t	0.401***	0.332***	0.232***	0.188*
	(0.108)	(0.089)	(0.080)	(0.098)
Δage_t	-0.012	0.019	0.107	0.123*
	(0.069)	(0.062)	(0.076)	(0.069)
Δage_t^2	-0.004	-0.040	-0.140*	-0.158**
	(0.070)	(0.065)	(0.079)	(0.073)
$\Delta fsize_t$	-1.011	-0.870	-2.875	-2.580
	(2.990)	(2.240)	(2.277)	(1.708)
$\Delta fsize_t^2$	0.596	0.484	1.337	1.171
	(1.448)	(1.064)	(1.112)	(0.830)
$HEF\ Index_t$		-0.288***		-0.250***
		(0.083)		(0.079)
Δq_t			0.170***	0.154***
			(0.043)	(0.034)
obs	31	31	31	31
R^2	0.51	0.61	0.64	0.71

Hetroskedasticity & serial correlation adjusted s.e. in parentheses; ***p<0.01, ** p<0.05, * p<0.1. Intercept not reported

Table 2: Aggregate FES consumption, GMM

	(1)	(2)	(3)	(4)
	baseline	*HEF*	*hp*	*HEF & hp*
coefficient				
r_t	0.326**	0.362***	0.426***	0.528***
	(0.140)	(0.114)	(0.141)	(0.117)
Δy_t	0.424***	0.338***	-0.034	0.048
	(0.154)	(0.129)	(0.117)	(0.113)
Δage_t	-0.035	-0.022	0.114***	0.139***
	(0.034)	(0.036)	(0.039)	(0.021)
Δage_t^2	0.020	0.002	-0.142***	-0.164***
	(0.036)	(0.037)	(0.051)	(0.024)
$\Delta fsize_t$	0.173	-0.677	-1.964	-1.574
	(2.622)	(1.460)	(1.760)	(1.269)
$\Delta fsize_t^2$	-0.079	0.390	0.706	0.614
	(1.243)	(0.684)	(0.836)	(0.630)
$HEF\ Index_t$		-0.308***		-0.333***
		(0.076)		(0.053)
Δq_t			0.209***	0.193***
			(0.039)	(0.022)
obs	28	28	28	28
R^2	0.465	0.611	0.558	0.757

Heteroskedasticity & serial correlation adjusted s.e. in parentheses; ***p<.01, **p<.05, *p<.1; instrument list: second and third lags of consumption growth, disposable income growth, RPIX inflation and 3m Treasury Bill rate, first lag of HEF index and house price inflation. Intercept not reported.

Table 3: Aggregate FES consumption, GMM with ONS instruments

coefficient	(1) *baseline*	(2) *HEF*	(3) *hp*	(4) *HEF & hp*
r_t	0.350***	0.395***	0.490***	0.536***
	(0.116)	(0.072)	(0.156)	(0.117)
Δy_t	0.674***	0.451***	0.188	0.008
	(0.119)	(0.096)	(0.133)	(0.097)
Δage_t	-0.075	-0.033	0.084*	0.156***
	(0.047)	(0.042)	(0.050)	(0.028)
Δage_t^2	0.073	0.020	-0.108*	-0.183***
	(0.050)	(0.045)	(0.055)	(0.030)
$\Delta fsize_t$	3.371	0.920	-1.375	-1.459
	(3.220)	(2.322)	(1.477)	(1.594)
$\Delta fsize_t^2$	-1.366	-0.296	0.546	0.521
	(1.520)	(1.076)	(0.686)	(0.762)
$HEF\ Index_t$		-0.319***		-0.364***
		(0.072)		(0.045)
Δq_t			0.173***	0.208***
			(0.045)	(0.022)
obs	28	28	28	28
R^2	0.404	0.611	0.621	0.752

Hetroskedasticity & serial correlation adjusted s.e. in parentheses: ***p<.01, **p<.05, *p<.1; Instrument list: ONS consumption growth and disposable income growth, second and third lags of RPIX inflation and 3m Treasury Bill rate, Intercept not reported.

Table 4: Robustness - aggregate ONS consumption

	(1)	(2)	(3)	(4)
	baseline	*HEF*	*hp*	*HEF & hp*
coefficient				
r_t	-0.028	0.404	0.510**	0.976**
	(0.457)	(0.625)	(0.239)	(0.384)
$\Delta y_{c,t}$	0.877***	0.429	0.172	-0.108
	(0.323)	(0.518)	(0.276)	(0.273)
$\Delta age_{c,t}$	-0.075*	-0.070**	0.044	0.058
	(0.039)	(0.035)	(0.045)	(0.043)
$\Delta age^2_{c,t}$	0.094**	0.093**	-0.042	-0.056
	(0.041)	(0.037)	(0.050)	(0.047)
$\Delta fsize_{c,t}$	5.521	3.876	0.688	-1.379
	(3.586)	(3.873)	(2.028)	(2.004)
$\Delta fsize^2_{c,t}$	-2.821	-1.825	-0.325	0.816
	(1.876)	(2.101)	(1.037)	(1.049)
$HEF\ Index_t$		-0.1921		-0.174***
		(0.111)		(0.064)
Δq_t			0.223***	0.237***
			(0.044)	(0.048)
obs	27	27	27	27
R^2	0.424	0.407	0.620	0.584

Heteroskedasticity & serial correlation adjusted s.e. in parentheses; ***p<.01, **p<.05, *p<.1; instrument list: second and third lags of consumption growth, disposable income growth, RPIX inflation and 3m Treasury Bill rate, first lag of HEF index and house price inflation. Intercept not reported.

Table 5: Robustness - aggregate FES non-durables consumption

coefficient	(1) *baseline*	(2) *HEF*	(3) *hp*	(4) *HEF & hp*
r_t	0.267***	0.168**	0.232***	0.150**
	(0.062)	(0.073)	(0.047)	(0.058)
$\Delta y_{c,t}$	0.330***	0.276***	0.179**	0.145
	(0.100)	(0.089)	(0.071)	(0.085)
$\Delta age_{c,t}$	0.010	0.034	0.117*	0.129**
	(0.055)	(0.053)	(0.059)	(0.057)
$\Delta age^2_{c,t}$	-0.023	-0.052	-0.145**	-0.159**
	(0.056)	(0.057)	(0.062)	(0.060)
$\Delta fsize_{c,t}$	-0.824	-0.712	-2.495	-2.266
	(2.473)	(2.353)	(1.993)	(2.038)
$\Delta fsize^2_{c,t}$	0.304	0.215	0.969	0.840
	(1.182)	(1.107)	(0.937)	(0.958)
$HEF\ Index_t$		-0.228***		-0.194**
		(0.078)		(0.073)
Δq_t			0.153***	0.140***
			(0.036)	(0.025)
obs	31	31	31	31
R^2	0.56	0.63	0.68	0.73

Hetroskedasticity & serial correlation adjusted s.e. in parentheses; ***p<0.01, ** p<0.05, * p<0.1. Intercept not reported

Table 6: Disaggregated consumption, OLS

coefficient	(1) *baseline*	(2) *HEF*	(3) *hp*	(4) *HEF & hp*	(5) *interaction*
r_t	0.355***	0.209***	0.293***	0.159**	0.178**
	(0.030)	(0.044)	(0.027)	(0.042)	(0.055)
$\Delta y_{c,t}$	0.475***	0.454***	0.422***	0.408***	0.409***
	(0.053)	(0.046)	(0.064)	(0.059)	(0.061)
$\Delta age_{c,t}$	-0.064	-0.040	-0.019	0.004	-0.004
	(0.062)	(0.082)	(0.054)	(0.074)	(0.076)
$\Delta age^2_{c,t}$	0.007	-0.021	-0.036	-0.064	-0.057
	(0.107)	(0.112)	(0.092)	(0.097)	(0.099)
$\Delta fsize_{c,t}$	0.520	0.689	0.369	0.527	0.558
	(0.468)	(0.465)	(0.600)	(0.598)	(0.621)
$\Delta fsize^2_{c,t}$	-0.328	-0.441*	-0.310	-0.416	-0.418
	(0.213)	(0.196)	(0.272)	(0.258)	(0.270)
$HEF\ Index_t$		-0.321**		-0.289**	-0.024
		(0.105)		(0.099)	(0.057)
Δq_t			0.100**	0.100**	0.100**
			(0.031)	(0.034)	(0.037)
HEF_t*coh46-50					-0.363***
					(0.042)
HEF_t*coh51-55					-0.303***
					(0.059)
HEF_t*coh56-60					-0.212**
					(0.074)
HEF_t*coh61-65					-0.326**
					(0.115)
HEF_t*coh66-70					-0.740***
					(0.148)
obs	159	156	159	156	156
R^2	0.51	0.54	0.53	0.56	0.57

Clusters in birth cohort-adjusted standard errors in parentheses; ***p<.01, **p<.05, *p<.1; cohxx-yy is a dummy taking value one if the birth year is between xx and yy, and zero otherwise; coefficients on cohort dummy variables and cohort specific time trends not reported.

Table 7: Disaggregated consumption, GMM

coefficient	(1) *baseline*	(2) *HEF*	(3) *hp*	(4) *HEF & hp*	(5) *interaction*
r_t	0.381***	0.532**	0.635***	0.824***	0.845***
	(0.146)	(0.230)	(0.169)	(0.238)	(0.240)
$\Delta y_{c,t}$	0.504***	0.394***	-0.068	-0.016	-0.057
	(0.120)	(0.131)	(0.157)	(0.128)	(0.136)
$\Delta age_{c,t}$	0.130	0.238*	0.323*	0.348**	0.353**
	(0.135)	(0.129)	(0.178)	(0.166)	(0.162)
$\Delta age^2_{c,t}$	-0.201	-0.318**	-0.383*	-0.402**	-0.394**
	(0.150)	(0.147)	(0.205)	(0.192)	(0.185)
$\Delta fsize_{c,t}$	0.577	0.743	0.087	0.175	0.376
	(0.608)	(0.649)	(0.884)	(0.883)	(0.900)
$\Delta fsize^2_{c,t}$	-0.335	-0.476	-0.443	-0.454	-0.556
	(0.309)	(0.344)	(0.414)	(0.409)	(0.426)
$HEF\ Index_t$		-0.200**		-0.193**	0.006
		(0.089)		(0.092)	(0.188)
Δq_t			0.195***	0.151***	0.155***
			(0.040)	(0.031)	(0.029)
HEF_t*coh46-50					–0.413
					(0.261)
HEF_t*coh51-55					-0.110
					(0.266)
HEF_t*coh56-60					0.328
					(0.361)
HEF_t*coh61-65					-0.662**
					(0.276)
HEF_t*coh66-70					-0.532*
					(0.276)
obs	141	135	141	135	135
R^2	0.50	0.53	0.37	0.43	0.44

Heteroskedasticity & serial correlation adjusted s.e. in parentheses;***p<.01,**p<.05, *p<.1; cohxx-yy is a dummy taking value one if the birth year is between xx and yy, and zero otherwise; coefficients on cohort dummy variables and cohort specific time trends not reported; instrument list: see Table 2.

Table 7: continued

coefficient	(6) *interaction with income*
r_t	0.778***
	(0.237)
$\Delta y_{c,t}$	-0.343
	(0.446)
$\Delta age_{c,t}$	-0.396**
	(0.177)
$\Delta age^2_{c,t}$	0.507**
	(0.218)
$\Delta fsize_{c,t}$	1.280
	(0.933)
$\Delta fsize^2_{c,t}$	-0.850*
	(0.470)
Δq_t	0.106***
	(0.029)
$\Delta y_{c,t}$*coh46-50	0.525
	(0.414)
$\Delta y_{c,t}$*coh51-55	0.520
	(0.401)
$\Delta y_{c,t}$*coh56-60	0.601
	(0.459)
$\Delta y_{c,t}$*coh61-65	0.656
	(0.450)
$\Delta y_{c,t}$*coh66-70	0.910**
	(0.456)
obs	138
R^2	0.46

Table 8: Disaggregated consumption, GMM with ONS instruments

coefficient	(1) *baseline*	(2) *HEF*	(3) *hp*	(4) *HEF & hp*	(5) *interaction*
r_t	0.503***	0.771***	0.630***	0.937***	0.928***
	(0.126)	(0.192)	(0.143)	(0.213)	(0.213)
$\Delta y_{c,t}$	0.556***	0.359***	0.054	-0.049	-0.108
	(0.108)	(0.120)	(0.122)	(0.129)	(0.137)
$\Delta age_{c,t}$	0.066	0.183	0.287*	0.380**	0.409**
	(0.124)	(0.124)	(0.153)	(0.166)	(0.166)
$\Delta age^2_{c,t}$	-0.125	-0.251*	-0.344*	-0.436**	-0.467**
	(0.136)	(0.143)	(0.180)	(0.197)	(0.197)
$\Delta fsize_{c,t}$	-0.060	0.091	-0.120	-0.347	-0.112
	(0.572)	(0.693)	(0.828)	(0.959)	(0.993)
$\Delta fsize^2_{c,t}$	-0.015	-0.178	-0.269	-0.221	-0.375
	(0.278)	(0.347)	(0.384)	(0.438)	(0.466)
$HEF\ Index_t$		-0.182**		-0.135	0.080
		(0.090)		(0.095)	(0.190)
Δq_t			0.163***	0.151***	0.163***
			(0.032)	(0.033)	(0.034)
HEF_t**coh*46-50					-0.418
					(0.276)
HEF_t**coh*51-55					-0.128
					(0.274)
HEF_t**coh*56-60					0.447
					(0.395)
HEF_t**coh*61-65					-0.781***
					(0.291)
HEF_t**coh*66-70					-0.431
					(0.298)
obs	141	135	141	135	135
R^2	0.49	0.52	0.43	0.41	0.40

Heteroskedasticity & serial correlation adjusted s.e. in parentheses;***p<.01,**p<.05, *p<.1; coh*xx-yy* is a dummy taking value one if the birth year is between xx and yy, and zero otherwise; coefficients on cohort dummy variables and cohort specific time trends not reported; instrument list: see Table 3.

Table 9: Robustness: disaggregate consumption by birth cohort and age

	(1)	(2)	(3)	(4)	(5)
	baseline	*HEF*	*hp*	*HEF & hp*	*interaction*
coefficient					
r_t	0.340***	0.195***	0.266***	0.144**	0.155**
	(0.028)	(0.052)	(0.035)	(0.049)	(0.061)
$\Delta y_{c,t}$	0.465***	0.455***	0.418***	0.415***	0.415***
	(0.058)	(0.051)	(0.055)	(0.050)	(0.054)
$\Delta age_{c,t}$	-0.006	0.014	0.041	0.057	0.061
	(0.038)	(0.044)	(0.033)	(0.040)	(0.044)
$\Delta age^2_{c,t}$	-0.020	-0.046	-0.079**	-0.100**	-0.100**
	(0.037)	(0.038)	(0.028)	(0.034)	(0.036)
$\Delta fsize_{c,t}$	0.608	0.754	0.503	0.630	0.704
	(0.443)	(0.438)	(0.522)	(0.516)	(0.572)
$\Delta fsize^2_{c,t}$	-0.396*	-0.486**	-0.395	-0.473*	-0.509*
	(0.205)	(0.184)	(0.237)	(0.214)	(0.255)
$HEF\ Index_t$		-7.581**		-6.703**	-1.108
		(2.340)		(2.210)	(1.622)
Δq_t			0.103**	0.099**	0.099**
			(0.034)	(0.039)	(0.039)
HEF$_t$*coh46-50					-0.329***
					(0.036)
HEF$_t$*coh51-55$_{\text{young}}$					-0.367***
					(0.041)
HEF$_t$*coh51-55$_{\text{old}}$					-0.061
					(0.133)
HEF$_t$*coh56-60$_{\text{young}}$					-0.349***
					(0.074)
HEF$_t$*coh56-60$_{\text{old}}$					0.240
					(0.127)
HEF$_t$*coh51-65					-0.255**
					(0.088)
HEF$_t$*coh66-70					-0.752***
					(0.101)
obs	165	162	165	162	162
R^2	0.52	0.55	0.54	0.56	0.58

Clusters in birth cohort-adjusted standard errors in parentheses; ***p<.01, **p<.05, *p<.1; cohxx-yy is a dummy equal to one if the birth year is between xx and yy, and zero otherwise; coefficients on cohort dummy variables and cohort specific time trends not reported; young are people below 35.

Table 10: Robustness - disaggregated non-durables consumption

coefficient	(1) *baseline*	(2) *HEF*	(3) *hp*	(4) *HEF & hp*	(5) *interaction*
r_t	0.350***	0.247**	0.305***	0.212**	0.221**
	(0.052)	(0.069)	(0.057)	(0.072)	(0.074)
$\Delta y_{c,t}$	0.441***	0.420***	0.403***	0.389***	0.389***
	(0.043)	(0.040)	(0.047)	(0.044)	(0.046)
$\Delta age_{c,t}$	-0.130*	-0.119*	-0.097*	-0.088	-0.101*
	(0.051)	(0.055)	(0.047)	(0.049)	(0.046)
$\Delta age^2_{c,t}$	0.101	0.086	0.070	0.057	0.068
	(0.085)	(0.081)	(0.078)	(0.073)	(0.074)
$\Delta fsize_{c,t}$	0.570	0.673	0.460	0.562	0.595
	(0.479)	(0.524)	(0.560)	(0.596)	(0.634)
$\Delta fsize^2_{c,t}$	-0.364	-0.434	-0.350	-0.417	-0.423
	(0.214)	(0.238)	(0.251)	(0.268)	(0.279)
$HEF\ Index_t$		-0.241**		-0.220*	-0.019
		(0.092)		(0.090)	(0.054)
Δq_t			0.073**	0.069*	0.068*
			(0.024)	(0.028)	(0.031)
HEF_t*coh46-50					-0.271***
					(0.028)
HEF_t*coh51-55					-0.276***
					(0.045)
HEF_t*coh56-60					-0.091
					(0.069)
HEF_t*coh61-65					-0.290**
					(0.084)
HEF_t*coh66-70					-0.557**
					(0.161)
obs	159	156	159	156	156
R^2	0.52	0.54	0.54	0.55	0.56

Clusters in birth cohort-adjusted standard errors in parentheses; ***p<.01, **p<.05, *p<.1; coh*xx-yy* is a dummy taking value one if the birth year is between xx and yy, and zero otherwise; coefficients on cohort dummy variables and cohort specific time trends not reported.

Table 11: SML data - descriptive statistics

variable	*mean*	*min*	*max*	*st dev*
spread	1.213	-1.469	13.375	1.223
loan	10.375	6.551	13.777	0.779
value	10.674	7.090	13.815	0.816
income	9.626	6.215	13.815	0.712
age	3.454	2.890	4.554	0.277

All variables, except *spread*, are in logarithms

Table 12: FES data - cohort definition and cell size

cohort	*birth*	*age in 1975*	*age in 2005*	*cell size minimum*	*cell size maximum*	*cell mean*	*# years*
1	1940-44	31-35	61-65	141	702	573	31
2	1945-49	26-30	56-60	169	848	700	31
3	1950-54	21-25	51-55	156	715	626	31
4	1955-59	16-20	46-50	145	739	635	28
5	1960-64	11-15	41-45	168	817	686	23
6	1965-69	6-10	36-40	177	785	635	18

Table 13: FES data - descriptive statistics

variable	*mean*	*min*	*max*	*st dev*
$\Delta c_{i,t}$	1.64	-8.36	13.46	4.60
$\Delta y_{i,t}$	2.27	-15.20	20.29	5.57
r_t	3.03	-11.81	8.01	3.31
Δq_t	3.17	-14.55	15.87	8.88

All variables are in log differences (except r_t) times 100