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Content

Editorial

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The fourth 2016 issue of the Banco de Portugal Economic Studies contains four diverse essays. The first two essays take as subject of analysis the households, with the first providing an analysis of precautionary savings and the second an in-depth characterization of the distribution of assets (and liabilities). The third essay studies firms´ decisions to switch banks. The fourth covers new techniques for nowcasting aggregate tourism indicators.

The first paper, by V. Ercolani, is entitled "The precautionary saving: theories, measurements and policies". One of the most interesting household behavior patterns in several countries during the Great Recession was an increase in the savings rate. One interpretation of this finding is that it constitutes a defensive reaction to the greater uncertainty experienced by households due to higher unemployment rates and income volatility after 2008. Ercolani reviews the models where precautionary savings emerge and the risks that trigger that type of savings. Fundamentally, the presence of uncertainty is not enough to generate precautionary savings. Households must be in at least one of two situations: preferences must be characterized by prudence, where expected future marginal utility of consumption increases with the variance of future income or they must fear being pushed against borrowing constraints. In both cases, households want to create a buffer of savings that insures them against several risks. Many types of risks are relevant, both at the individual level such as risky labor income and employment, health shocks or changes in family composition and at the aggregate level, since we know that business cycles influence the distribution of individual risks.

A second part of Ercolani's essay deals with the results of empirical studies and evaluates the relative importance of the precautionary motive in total savings. For example, empirically the pace at which the elderly decumulate their savings is lower than what simple life cycle models predict. Besides a possible bequest motive, keeping wealth at relatively high values could be explained as a precaution given the possible need to make unexpected expenditures, for instance to deal with a health problem.

All in all, precautionary savings can be quite large. Some estimates indicate that the precautionary saving motive can account for about 30% of the aggregate saving rate.

A third part of the paper explores the relevance of precautionary savings for fiscal and monetary policies. Results show that precautionary savings and the interaction of these with the existence of borrowing constraints lead economic agents with low levels of wealth to have a high marginal propensity to consume out of wealth. If these households are the target of transfers financed by issuing public debt there is a violation of Ricardian equivalence, i.e. there will be increases in consumption and in aggregate demand. This result suggests a microeconomic foundation for why fiscal multipliers are positive. Another interesting conclusion of the literature is that public expenditures that reduce household risks (for example a reinforcement of unemployment insurance schemes) may induce households to reduce accumulated precautionary savings thus generating an expansionary effect on aggregate consumption.

The second essay in this issue is "Financial situation of the households in Portugal: an analysis based on the HFCS 2013" by S. Costa. This paper consists of a detailed descriptive analysis of the data from the second wave of the Portuguese Household Finance and Consumption Survey conducted in 2013. Two types of results are reported: the first includes summary measures of the distribution of assets, liabilities and net assets across Portuguese households. The second is a series of comparisons with earlier data showing how some of the main variables of interest have changed since the first wave of the survey in 2010.

The median value of the net wealth (difference between the value of assets and liabilities) of the Portuguese households was around 71 thousand euros, with the mean being 156 thousand euros. Slightly more than 50 per cent of the total net wealth is in the hands of 10 per cent of the households, illustrating the high concentration of this distribution. As in other countries, inequality of wealth is much larger than inequality of income. The Gini index for the net wealth stands at 68 percent. By comparison the income and consumption Ginis are 44 per cent and 32 percent, respectively.

As for the composition of wealth, on average, net wealth is 84.4 per cent of gross wealth meaning that debt is the remaining 15.6 per cent, an average with an underlying great deal of heterogeneity. Real wealth (including real estate, motor vehicles, self-employment businesses and other assets) is 88 per cent of gross wealth with the remaining 12 per cent in the form of financial wealth. For most households real estate is dominant: 75 per cent of the households are owners of the main residence and about 30 per cent have loans using it as collateral.

Regarding the distribution of wealth components, inequality is significantly higher in the case of financial wealth than real wealth. As for debt, it has a very skewed distribution which is driven by the fact that more than 50 per cent of households do not have any debt.

Comparing the survey's first wave in 2010 with the second wave in 2013 the main results indicate that median net wealth declined but that inequality increased slightly. The value of properties declined for most households. The effect on net wealth was, however, mitigated for most households by a reduction in the amounts of debt outstanding. The percentage of households holding debt remained stable and the median value of debt declined for all types of households but more importantly for those in the higher wealth classes. Nevertheless, the fraction of vulnerable households, those with high levels of debt relative to their financial situation, remained high. However, the decline in interest rates contributed to a reduction in the burden of the debt service on income.

The third paper, by G. Nogueira, is entitled "Bank switching in Portugal". In countries like Portugal a direct use of financial markets by firms is relatively rare and typically limited to the largest firms. In this context, the banking relationships of firms are paramount. A steady relationship with a bank can help overcome asymmetric information problems and facilitate contract flexibility and the access of firms to credit as well as improve the conditions under which the credit is provided such as lower interest rates or collateral requirements. However, we do observe numerous instances where firms switch banks. Why does this happen and what is the significance of this switch? Nogueira's paper tackles these questions by surveying the relevant literature and by conducting an empirical analysis with a very thorough dataset.

The literature surveyed by Nogueira raises the issue that banking relationships may also have negative effects for firms. Against the benefits that stem from the reduction of asymmetric information problems already mentioned there is also the possibility that over time banks acquire valuable information and bargaining power in their dealings with firms and that they may use this to their own advantage. These hold up costs are usually reflected in higher interest rates. In this case we see why, in some circumstances, firms may want to switch or at least diversify their banking relationships. These incentives will be stronger if competition among banks is intense, thereby reducing their power to control firms and extract rents.

Nogueira's empirical work is based on a dataset collating data from three separate sources: a national credit register database, a database on company and accounting data and a database with monetary and financial statistics covering banks. Between 1990 and 2008 the number of switches increases but that seems to be driven mostly by an increasing participation of firms in the financial system given that the proportion of firms in the data switching is relatively stable at around 11%. After 2008 both the number of switches and the proportion of firms switching decline significantly.

Comparing switching versus non-switching banking relationships, Nogueira shows that switching firms are older, larger, with more transparent financial information and less leveraged. Switching firms are more likely to have longer relationships and in greater number.

Nogueira continues the empirical work by estimating regressions explaining the probability that a firm switches bank in any period as a function of the characteristics of the firm, of the incumbent bank, of the relationship itself and of macroeconomic variables. The results from the regression analyses tell us that larger, older, higher growth and higher rates of return firms are more likely to switch banks as are firms having a longer bank relationship. On the other hand a measure of financial opaqueness or being in an aggregate downturn period is negatively related to switching. An extra percentage point in GDP growth proportionally increases the probability of switching by 5 per cent.

Of the many results obtained by Nogueira one stands out: firms are more likely to switch from longer relationships. This leads us to consider that the balance of the advantages and disadvantages to a firm of maintaining a banking relationship change over time. Naturally this highlights the benefits of competition and availability of choice in the banking industry and should serve as a reminder of the value of promoting that competition.

The fourth and last paper in this issue of Estudos Económicos, by S. Cabral and C. Duarte, is entitled "Nowcasting portuguese tourism exports". This essay focuses on two different areas attracting the attention of policymakers. The first is the tourism industry and its relevance for the Portuguese economy as a major exporter of services. The second is the use of short term forecasting techniques to conduct nowcasting, to assist in the monitoring of economic activity. There is no question that tourism is a growth area for the Portuguese economy but tourism is also, but its own nature, an activity prone to high volatility as shocks in weather patterns, international events and political or economic developments in the markets of origin get translated into potentially large swings in demand.

Given these circumstances the availability of good monitoring tools is particularly relevant in the case of tourism and that is precisely what the Cabral and Duarte paper deals with. In the paper the authors focus on nowcasting developments in the quarterly exports of tourism, as reported in the National Accounts. The question is how to combine data with different time frames, for example series of monthly released data (such as non-resident overnight stays or ATM transactions with cards issued abroad) with quarterly data to improve the quality of the forecasts for the quarter.

Cabral and Duarte study the performance of several mixed-frequency methodologies including bridge models and Mixed Data Sampling (MIDAS) regressions and also more traditional auto-regressive techniques. They use data from October 2000 to March 2016 and conduct a recursive pseudo real-time exercise of forecasting using the alternative techniques and following the release pattern of the indicators that occur in real-time situations. Nowcast accuracy is quantified by using used the root mean squared forecast errors (RMSE). Overall, MIDAS models tend to fare better than traditional bridge models for the majority of the predictors and evaluation periods. The best performing nowcast is always obtained from a combination of projections of a MIDAS variant with autoregressive dynamics which suggests the use of this class of mixed-frequency models for the short-term forecasting of tourism exports.

The precautionary saving: theories, measurements and policies

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Abstract
This article focuses on one particular form of saving, the precautionary saving. To this end, a simple theoretical framework is presented within which such a form of saving arises. Next, the potential risks triggering the precautionary saving are discussed. As a second step, examples which highlight the empirical importance of the precautionary saving are provided. Finally, it is shown how the precautionary motive can heavily influence the effects of both fiscal and monetary policies. (JEL: D10, E21, E52, E62)

Introduction

During the last decade, most of the industrialized countries lived periods where both the degree of uncertainty and the households' saving rates were high. For example, the Great Recession has been characterized by a high level of unemployment which raised both the risk of job losses and the unemployment duration. Meanwhile, households' saving has increased (see Carroll *et al.* 2012; Mody *et al.* 2012). Such an economic phase has contributed to revive the interest in studying the determinants of saving decisions and, in particular, the connection between saving dynamics and uncertainty.

Investigating on why people save is a long-standing issue in the literature. Among others, let me mention the intertemporal motive which pushes individuals to postpone consumption because of patience or returns to saving. Let me then cite the smoothing motive which allows individuals to smooth consumption over time. Further, there is the bequest motive. Finally, I refer to the *precautionary motive* which was already defined by Keynes (1936) as a way *to build up a reserve against unforeseen contingencies*.

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This paper discusses some theories, empirical findings and policy implications related to the last cited saving motive within the household sector. It is worth noting that most of the work on precautionary saving focuses on the US economy, hence, if not differently specified, the described papers will refer to the United States.

The article has the following structure. In the first part, I sketch a simple theoretical framework from which the precautionary saving motive arises and present the most common risks that trigger a precautionary saving behavior. In the second part, I highlight the empirical importance of precautionary saving. I present the precautionary saving motive as a device for solving well known empirical puzzles. Further, I describe papers which provide a quantitative assessment of such a form of saving. In the last part, I describe how the effects of both fiscal and monetary policies can be influenced by the form of saving under scrutiny. I then conclude.

Saving for precautionary motives: theories and causes

This section recalls a simple theoretical framework within which the precautionary saving motive is at work. The section also spells out the most known risks triggering such a form of saving.

Sketching a theoretical framework

Consider a theoretical framework similar to those presented in Hall *et al.* (1978), Zeldes (1989) or Deaton (1992), which embeds the permanent income hypothesis (PIH).[1] In practice, this dynamic model for households has the following features:[2]

1. A time-separable quadratic utility function (with consumption as the only argument);[3]
2. An exogenous and stochastic labor income process;

1. Offering an exhaustive list of papers that deals with the PIH is beyond our scope. However, notice that already Friedman (1957) provided qualitative descriptions of the PIH. Additional important papers are Leland (1968) and Caballero (1990).

2. This framework considers the households' behavior as summarized by the behavior of a representative agent. Afterwards, I present versions of the PIH model which rigorously take into account households' heterogeneity.

3. Using such a utility function has the advantage of mathematical tractability, whereas it presents the disadvantage of being unrealistic since, after a certain level of consumption, an increase in consumption itself produces a decrease in welfare. Time separability implies that the utility that consumption yields today does not depend on the levels of consumption in other periods.

3. The presence of a single asset whose yield is deterministic (or exogenous) and independent from the income realization;[4]
4. A terminal condition which rules out Ponzi schemes;[5]
5. No bequest motives.

The crucial reason for saving in this economy is the smoothing motive. Other than condition (4), there are no constraints on borrowing and households may borrow and lend freely at the riskless interest rate in order to smooth consumption through income shocks. In particular, they will keep their marginal utility of consumption constant over time, implying that, at any date, the optimal level of consumption is the permanent income. The permanent income is the annuity value of the discounted flows of income and assets (human and financial wealth). This consumption level satisfies *certainty equivalence*, meaning that the variance and higher order moments of the income process do not matter for the determination of consumption.[6] Put it differently, the precautionary saving motive cannot be active in this framework despite the presence of income uncertainty.

To generate the *precautionary saving* — the extra saving accumulated to hedge against the occurrence of future income shocks — either condition (1) or condition (4), or both, need to be relaxed.[7] For example, using more realistic utility functions, e.g., the constant relative risk aversion (CRRA) or the constant absolute risk aversion (CARA) functions, is a sufficient condition for generating a precautionary saving motive. In particular, Kimball (1990) shows that the precautionary saving is active if agents display *prudence*, that is the third derivative of the utility function is positive.[8] Another element triggering precautionary saving is the presence of binding borrowing constraints. When agents face borrowing constraints they fear receiving bad income realizations which would push them towards the constraint, a place where they loose the possibility of smoothing consumption. In order to avoid that, they accumulate some precautionary saving.

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4. This hypothesis recalls the existence of incomplete financial markets. In these markets, the assets returns are not state contingent to the income realizations. The diametrically opposite benchmark is having complete markets where a full set of state contingent assets is available to the agents.

5. This condition implies that agents cannot die with a positive level of debt.

6. Intuitively, the certainty equivalence principle establishes that an individual living in a stochastic economy acts as if the economy was deterministic.

7. Notice that that the precautionary saving can also be labeled as (saving for) *self-insurance*. That is, the absence of other insurance opportunities induces the agents to adjust their asset holdings to acquire self-insurance.

8. Prudence can be broadly defined as a measure of the sensitivity of the consumption choice to risk. If prudence is nil, then uncertainty does not have any possibility of influencing the individual choices through preferences.

Summing-up: a stochastic environment is not sufficient to generate a precautionary saving motive. On top of a stochastic economy, we also need that either the participants to this economy are prudent or constraints that could limit the households' borrowing capacity.

Sources of risk

In the previous section, I highlighted an extremely simple model which embeds two types of risk. These are the labor income uncertainty and the probability for a household to become borrowing constrained. Obviously, more complex and richer models are able to capture many other sources of risk observed in reality.

First of all, labor income uncertainty can be generated not only by an exogenous stochastic flow as described above, but also by shocks to the employment status or to the human capital (see the models developed in Low 2005; Huggett *et al.* 2011). Second, there are other realistic sources of risks, such as (i) health risks, (ii) shocks to families or (iii) to capital. For example, health shocks may impact on the dynamics of individual earnings, utility and life's length which, in turn, influence the agents' saving behaviour (see Palumbo 1999; Attanasio *et al.* 2010). Also changes in the family composition such as marriage, divorce, and the birth of children may affect the saving dynamics; Cubeddu and Ríos-Rull (2003) show that marital status risk can represent an important source of precautionary saving. Finally, the return to financial capital and the house prices are risky. In particular, the latter, which represent a major component of households' portfolios, have a large idiosyncratic component associated to geographical location (see Davis and Heathcote 2007).

Another source of risk is represented by potential correlations among the risks cited above. For example, a bad health shock to the household head, such as a serious disease or an accident, can decrease the individual productivity or even generate a job displacement which, in turn, decreases the probability of generating children.

So far, I focused on risks occurred at the individual level. However, even the business cycle can represent a cause for a precautionary saving behavior. For example, if the aggregate state of the economy influences the conditional distribution of a specific idiosyncratic risk then a time-varying precautionary saving may occur. Davis and von Wachter (2011) show that earnings losses from job displacement roughly double if they occur in a recession as opposed to an expansion. Further, Guvenen *et al.* (2014) show that the worst income realizations are more likely in a recession.

The empirical importance of precautionary saving

This sections has two aims. First, it shows that the precautionary saving motive is a good candidate to solve well known empirical puzzles within the literature that studies optimal consumption dynamics. Second, it provides some measurements for the saving due to precautionary purposes.

Some puzzles for certainty-equivalence models

I here discuss two facts which are hard to explain within a model with certainty equivalence. These are (i) the excess sensitivity of consumption to transitory income innovations and (ii) the saving behavior of the elderly.[9]

The precautionary saving motive can help explain these puzzles. In order to understand fact (i), let me ask the following question: how does the precautionary saving motive shape the consumption policy function?[10] Figure 1 presents two typical consumption policy functions: one obtained from a PIH model with certainty equivalence (dashed line) and the other generated within a PIH model with a role for precautionary saving (solid line). The first policy function is increasing and linear in wealth. The second one, which lies below the other one, is increasing but concave.[11] This happens because the precautionary motive depresses consumption at any level of wealth, however, it depresses it more at low levels of wealth since the higher is the wealth the easier is bearing the effect of future uncertainty. Put simply, uncertainty makes people consume less and save more on average, but their spending becomes 'more sensitive' to an extra dollar of wealth. Such a sensitivity, defined as the marginal propensity to consume out of wealth (MPC), becomes higher as wealth declines or, equivalently, as wealth approaches the borrowing constraint.[12] Unlike it, the certainty-equivalence version of the model generates a constant or wealth-invariant MPC.

Regarding fact (ii), the implication of a life-cycle version of the certainty-equivalence PIH model is that people should accumulate wealth in their first

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9. The definition of excess sensitivity used here is the one in Hall and Mishkin (1982). They define excess sensitivity as the difference between the actual response in consumption and the reaction in the permanent income that occur as the result of a transitory income innovation. It has to be said that this definition differs from the one in Flavin (1981) under which consumption is excessively sensitive to income if it reacts to anticipated changes in income.

10. The consumption policy function, resulting from solving an economic model, can be broadly defined as a law that assigns an optimal level of consumption for any current level of wealth, conditional on a particular income realization.

11. Notice that Figure 1 does not have a quantitative objective. It just describes the typical shapes of two different policy functions.

12. Notice two things here. First, the MPC is the slope of the policy function. Hence, for a non-linear policy function, this slope varies with wealth. Second, Figure 1 depicts a borrowing constraint. At this constraint the (net) wealth is typically negative. However, it is common to see models where borrowing is not permitted; in those cases the borrowing limit is set to zero.

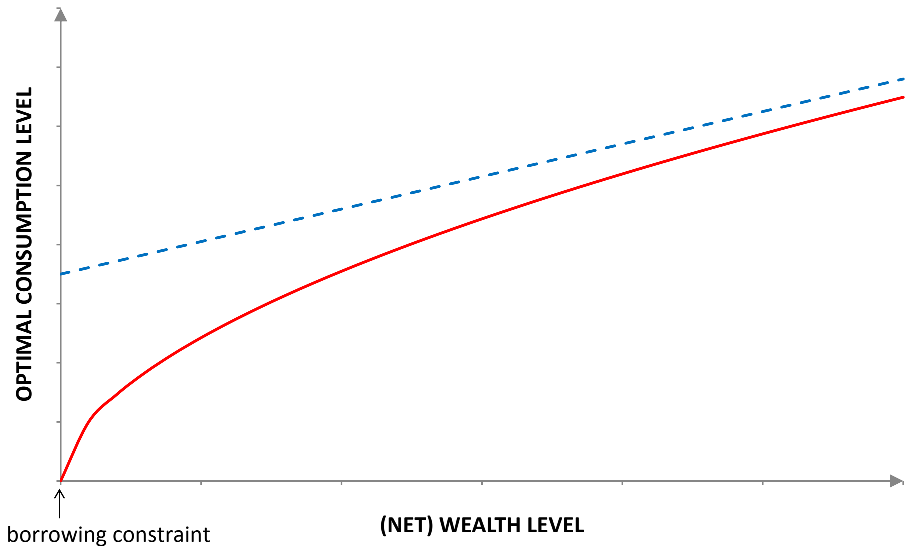

FIGURE 1: Typical shapes of two consumption policy functions. The dashed line mimics a policy function of a PIH model with certainty equivalence. The solid line mimics a policy function of a PIH model with a role for precautionary saving. The borrowing constraint represents a lower bound for the individual net wealth, meaning that agents cannot borrow beyond that value. Based on Zeldes (1989) and Carroll and Kimball (1996).

part of life while decumulating it during old age. The second part of the sentence has been tested empirically since the seventies. Mirer (1979) use cross-sectional data to show that assets do not run down during old age; conversely Hurd (1987), using panel data, argues that the wealth of elderly families does decline over time. Subsequently, both Modigliani (1988) and Kotlikoff (1988) agree on the following concept: elderly people do not drawn down their wealth as intensively as predicted by a life-cycle model with certainty equivalence and no bequest motives. On top of bequests and the uncertainty related to the moment of death, a precautionary saving motive can help solve this puzzle. Intuitively, the possibility of getting serious illness, with important associated costs for treatments, can be a crucial source of uncertainty for the elderly. Hence, old age households can keep part of their wealth as a buffer for the occurrence of these health shocks. De Nardi *et al.* (2010) estimate that the risk of incurring in high medical expenses is a key driver for saving in the old age.

Measuring precautionary saving

There have been several attempts to test for the presence of the precautionary saving behavior within the household sector. Some authors estimate reduced form equations inspired by the class of PIH models with a role for precautionary saving. For example, Lusardi (1998) shows that various measures of wealth are positively and significantly correlated with a subjective measure of income risk (the probability of a job loss), controlling for many other individual characteristics. Other authors follow a more structural approach in the sense that they estimate one particular implication of the PIH model: the Euler equation.[13] Under the non-certainty-equivalence version of the model, the Euler equation includes also the expected consumption variance which embeds all the information that individuals have on their future risks. Both Jappelli and Pistaferri (2000) and Bertola *et al.* (2005) estimate an Euler equation by proxying such a consumption variance with the subjective variance of income calculated within the Survey on Household Income and Wealth (SHIW), an Italian panel dataset. These authors find that the precautionary saving motive is active, implicitly rejecting the certainty-equivalence version of the PIH model.

Interestingly, Gourinchas and Parker (2001, 2002) estimate the whole PIH model, not only a single equation of it. This allows the authors to decompose household wealth in several components among which the share due to precautionary motives. Specifically, they use household survey data, like the Consumer Expenditure Survey (CEX) and PSID, and simulation techniques in order to estimate a version of the PIH model which explicitly accounts for age heterogeneity. They find that around 60% of nonpension liquid wealth is due to the precautionary motive. Such a form of saving is mostly generated by the behaviour of the young while, after age 45, households start to save mainly for retirement and bequest.

In the first part of the paper, I sketched a version of the PIH model with exogenous production, where the equilibrium interest rate is deterministic or exogenous, and with the presence of a representative agent. Aiyagari (1994) develops a general equilibrium model with heterogenous households, in terms of wealth and productivity, that behave as if they were in a PIH economy with a role for precautionary saving.[14] Next to the household sector, there is a representative firm which competitively maximizes profits. The resulting equilibrium interest rate equates the capital demanded by the firm with the (claims of) capital supplied by households. Within this framework,

13. The Euler equation is an equilibrium condition which typically describes the optimal allocation of consumption in two consecutive periods of time. Generally, the degree of patience, the returns to assets and the perceived uncertainty influence such an allocation.

14. It is worth recalling the pioneer paper of Bewley (1977) who proposed a model for the household sector where the heterogenous agents were subject to incomplete financial markets.

the author calculates the share of aggregate saving explained by income uncertainty. He shows that the level of precautionary saving heavily depends on some model parameters like for example the serial correlation of earnings. The higher is the value of the earnings persistence, the higher is the variance of the whole income process, hence the higher is the level of precautionary saving. For a relatively high degree of persistence, the precautionary saving motive can explain more than 30% of the aggregate saving rate.

Based on the standard version of the PIH model, agents cut consumption in order to increase their level of precautionary saving. Similarly, agents could save more by working harder. Pijoan-Mas (2006) extends the Aiyagari (1994) model by making labor supply endogenous and shows that individuals use also the work effort as a self-insurance mechanism. Quantitatively, he shows that aggregate consumption is 0.6% lower while work effort is 18% higher because of the presence of a precautionary saving motive.

There is a set of papers that study the precautionary saving over the business cycle. Carroll *et al.* (1992) and subsequently Carroll *et al.* (2012) invoke the precautionary saving motive to explain the tendency of saving to increase during recession. The last paper formulates a simple version of the PIH model with a role for income uncertainty and credit constraints and shows that saving reacts positively to a worsening in economic circumstances (such as an increase in the unemployment risk). Specifically, these papers show that the changes in the net wealth and labor income uncertainty can explain most of the business cycle fluctuations in personal saving, during and after the information technology and credit bubbles of 2001 and 2007. Using a model similar to Carroll *et al.* (2012), Mody *et al.* (2012) show that at least two-fifths of the increase in households' saving rate during the Great Recession (2007-2009) are explained by the increased uncertainty about labor income prospects. Unlike a certainty-equivalence model, Challe and Ragot (2016) show that a model with a role for precautionary saving is able to replicate the observed volatility of aggregate consumption. Finally, McKay (2016) incorporates a time-varying income risk, using the income process estimated by Guvenen *et al.* (2014), within an Aiyagari (1994) type of model. He shows that such a time-varying risk has an important effect on consumption and saving dynamics.[15]

15. He shows that market incompleteness raises the volatility of aggregate consumption by roughly 40%. Around half of this increase is due to changes in the income risk over the business cycle.

Policies and precautionary saving

This section presents a number of works that study the effects of fiscal and monetary policies within frameworks with a role for the precautionary saving motive.

Given the concepts discussed above, we should expect that the aggregate consumption reaction to a fiscal stimulus depends on the distribution of individuals across wealth levels and on their respective MPCs. Heathcote (2005) studies the effects of tax cuts within an Aiyagari (1994) type of model where private borrowing is not permitted. Among other things, he shows that a debt-financed transfers policy directed to all households has real effects in this economy, especially on consumption. This is because of the existence of a large fraction of individuals that are wealth-poor, i.e., they are pretty close to the borrowing limit, and hence have a high MPC. An important implication follows: the Ricardian equivalence does not hold in an economy with a role for precautionary saving and binding borrowing constraints.[16] Following this line of reasoning, Oh and Reis (2012) show that a targeted lump-sum transfers policy (where the transfers are directed to wealth-poor individuals) can have large expansionary effects for the aggregate demand. Finally, McKay and Reis (2016) focus on the role of fiscal automatic stabilizers and show that tax-and-transfers programs can have important effects on aggregate volatility.

There are some papers that focus on the effects of increases in government consumption, as opposed to monetary transfers, within various versions of the Aiyagari (1994) model. Among others, Brinca *et al.* (2016), using a life-cycle model show that differences in the distribution of wealth across countries generate differences in their respective aggregate responses to government expenditures.[17] Ercolani and Pavoni (2014), focusing on Italy, show that government expenditures in health can act as a form of consumption insurance for individuals subject to health shocks, thereby influencing their level of precautionary saving and, in turn, the size of fiscal multipliers.

Another stream of papers focuses on the role of public debt within an Aiyagari (1994) type of model. Aiyagari and McGrattan (1998) show that public debt can act as if it relaxed the household borrowing constraint. That is, higher levels of public debt result in higher interest rates making assets more attractive to hold and, hence, enhancing households' self-insurance possibilities. Challe and Ragot (2011) show that this channel can have important consequences for the effects of fiscal policy. They show that a debt-financed government spending policy could crowd in private

16. While Heathcote (2005) sets the borrowing constraint to zero, permitting borrowing does not generally invalidate such a conclusion unless the borrowing constraint is set at the *natural borrowing limit* (see chapter 9 of Ljungqvist and Sargent 2004, for details on this).

17. This result finds support in Carroll *et al.* (2014) who show that the MPC varies across countries.

consumption depending on the extent to which the fiscal policy influences the level of precautionary saving. Antunes and Ercolani (2016) focus on the endogeneity of the household borrowing constraint. They show that debt-financed government spending policies generate an upward pressure for the borrowing cost, hence favoring a tightening in the household borrowing limit which, in turn, affect the households' reactions to the policies.

Recently, some papers focus on the role of precautionary saving and household wealth heterogeneity conditional on the occurrence of monetary policy shocks. For example, Challe *et al.* (forthcoming) formulate and estimate a tractable model with heterogeneous agents, nominal frictions and uninsurable unemployment risk. In this context, a cut in the policy rate boosts aggregate demand which encourages job creation and lowers the perceived unemployment risk. Agents respond by decreasing their precautionary wealth which generates a rise in the consumption level. Further, Algan and Ragot (2010) show that the presence of binding borrowing constraint within an economy where the precautionary saving motive is active can invalidate the long-run neutrality of inflation on capital accumulation.

Conclusions

This article has described some theories, empirical exercises and policy implications associated to the precautionary saving motive. We have seen that such a form of saving has relevant empirical implications, both in explaining some empirical puzzles and in forming a non-negligible part of total saving. We have also seen that the the precautionary saving motive interacts with the effects of monetary and fiscal policies.

An important lesson follows. When doing policy evaluations, research should seriously consider using models with a role for precautionary saving. These models need to have incomplete financial markets. But, this is not the end of the story. For example, Kaplan and Violante (2010) show that there is *more insurance* beyond self-insurance.[18] Hence, even other mechanisms — like intra-household insurance, public insurance schemes or government redistribution — should be considered when studying the potential effects of fiscal and monetary policies.

18. This statement primarily refers to the insurance against the income shocks that have a permanent nature.

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Financial situation of the households in Portugal: an analysis based on the HFCS 2013

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Abstract
According to the Household Finance and Consumption Survey from 2013, the median value of the net wealth (i.e., the difference between the value of assets and liabilities) of the Portuguese households is around 71 thousand euros, which means that 50 per cent of the households have a lower level of net wealth. The top 10 per cent of households in terms of net wealth hold slightly more than 50 per cent of total net wealth, illustrating the high inequality of the net wealth distribution. For most households real estate has a dominant weight in their assets: 75 per cent of the households are owners of the main residence and about 30 per cent have loans using it as collateral. As compared to the first wave of the survey conducted in 2010, the value of real estate properties declined, contributing to a decrease in the value of household assets. The effect on net wealth was, however, mitigated by a reduction in the debt outstanding amounts. The degree of household indebtedness, measured by the ratio of debt to income or to assets, remained very high for a significant percentage of households. The decline in the Euribor rates contributed, however, to a reduction in the weight of the debt service on income. (JEL: C83, D10)

Introduction

This article presents the results of the second wave of the Portuguese Household Finance and Consumption Survey (HFCS, ISFF by its Portuguese acronym), which was conducted in 2013. The HFCS is the only statistical source in Portugal that permits relating assets, debt, income, consumption, demographic and socio-economic aspects as well as information about expectations and attitudes at the household level. This survey is part of a project promoted by the Eurosystem in order to collect comparable microeconomic data on the financial situation of households, and in particular on wealth among the euro area countries.[1]

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1. The ECB web page includes a wide range of information about the HFCS. The results for the euro area of the first wave of the survey were published by the ECB in 2013 (HFCN (2013a)

The HFCS methodology follows the principles agreed by participating countries but the implementation of the survey is decentralized at the national level. In Portugal, the survey is conducted by Banco de Portugal and Statistics Portugal. The main methodological aspects of the Portuguese HFCS are described in Appendix A. One important methodological characteristic is the sampling design. The sample is representative of the households living in Portugal and has a component that oversamples wealthy households. This sampling strategy is commonly used in wealth surveys and aims to obtain more efficient estimates of wealth given its highly asymmetric distribution in the population. The first wave of the Portuguese HFCS was conducted in 2010 and the third wave will be conducted in 2017. The results of the first wave for Portugal are described in Costa and Farinha (2012b).

As discussed in the next section, the HFCS data permits the analysis of the distributions of variables that affect the financial situation of households across different groups of households. This article focuses on these distributions. While it includes some data about income and consumption, the analysis focuses primarily on distributions of net wealth and its components (i.e. real assets, financial assets and debt), as it is for these variables that HFCS has a higher value added, when compared with other existing household surveys in Portugal. The article begins by describing the distributions of the main economic aggregates by household type obtained with HFCS 2013. Subsequently, the main characteristics of the distributions of net wealth and its components will be compared with those obtained with the HFCS 2010. Finally, given the high indebtedness level of the Portuguese households, data from two HFCS waves on debt burden, demand for credit, and credit constraints will also be compared. In the period between the HFCS 2010 and the HFCS 2013 significant changes occurred in the macroeconomic situation in Portugal, with negative impacts on the aggregate financial situation of the households. This makes the comparison of the two waves results particularly interesting.

Benefits and limitations of HFCS data

The HFCS data is very useful to study the behaviour of households, for example, in areas related to saving and consumption decisions, portfolio allocations, participation in debt, and liquidity constraints. This type of data can also be used to assess the impact of macroeconomic shocks or policy changes on different type of households. Additionally, the HFCS data contributes to a better understanding of the behaviour of macroeconomic

and HFCN (2013b)) and for the second wave will be published over the coming months (HFCN (2016a) and HFCN (2016b)).

aggregates, as it allows the identification of the groups of households where these aggregates are concentrated. Indeed, the ownership of certain assets, such businesses or sophisticated and risky financial products, are typically concentrated in a small number of households whose behaviour can dominate the aggregate evolution. In addition, as the recent financial crisis illustrated, information on the heterogeneity of the financial situation of households and, in particular, on the degree of indebtedness is essential to assess the extent to which debt accumulation in aggregate terms originates risks to financial stability and ultimately to the growth of economic activity.

The comparison of the aggregated HFCS data with the macroeconomic data from the National Accounts should be done with caution given the conceptual differences between the two sources and the measurement errors associated with both sets of information. A detailed analysis of the comparability issues is outside the scope of this article. Nonetheless, there are some general aspects which are important to refer here. In terms of concepts, one important difference stems from the fact that the HFCS refers to households, while the majority of macroeconomic data also includes Non-profit Institutions Serving Households. In terms of methodology, National Accounts have the advantage of using a comprehensive set of sources, many of which cover the whole population. However, for some items information on households is scarce and partly obtained as the residual of available data on the whole economy and other sectors. The HFCS has the advantage of collecting all information directly from the households in a coherent manner. Nevertheless, like any other survey, the HFCS is subject to reporting errors by households, which are difficult to identify and correct after the data collection. In particular, households' reluctance to reveal monetary values even when all the requirements regarding the confidentiality of data are provided for, can lead to underestimation of monetary values. In addition, although in the HFCS the wealthy households are oversampled (Appendix A), it is possible that a significant part of wealth, in particular of financial wealth, is not captured by the survey since it is concentrated in very few households which may not be part of the sample. In fact, in the Portuguese HFCS, as in many other wealth surveys, the amount of financial wealth is much lower than the Financial Accounts values, even for items which are relatively comparable between the two sources. For non-mortgage debt, the available data also suggest some underestimation of the HFCS values.

The above limitations directly affect the calculation of the levels but to a much lesser extent the distributions of the variables as well as the correlations between them. Thus the HFCS data should be primarily used for the purpose for which it was collected, i.e. for a microeconomic analysis of households' behaviour. As mentioned above, from a purely statistical point of view, this type of data is useful to infer the distribution of the variables in the population but does not substitute macroeconomic data to obtain the levels for the different economic aggregates.

Distributions of net wealth, income and consumption

The net wealth of a household is the difference between the value of its assets and its debts.[2] The HFCS data does not cover the accumulated rights over public and occupational pensions. As this type of asset is generally distributed more evenly than private wealth, its exclusion can lead to some overestimation of inequality in the wealth distribution.

Figure 1 compares the distributions of net wealth, income and consumption of non-durable goods and services obtained with the HFCS 2013 data for the Portuguese population.[3] These distributions show that net wealth is much more unequally distributed between households than income and that income is more unequally distributed than consumption. The top 10 per cent of households in terms of net wealth hold slightly more than 50 per cent of total net wealth. In the case of income and consumption, the top 10 per cent of households hold, respectively, slightly over 30 per cent and about 25 per cent of the total of these variables in the population. The Gini indexes for the net wealth, income and consumption stand at 68 percent, 44 per cent and 32 percent, respectively.

The higher inequality of wealth as compared to income and of income compared to consumption is consistent with the empirical evidence that shows that the saving rate increases with both income and wealth levels (Banco de Portugal (2016)). This behaviour can be reconciled with economic theory, for example, when the utility function of individuals depends on deviations of consumption from a basket of basic goods or when savings are a luxury good. The high positive skewness of net wealth may also be related with the fact that wealthier households can have more diversified portfolios with higher expected returns. Regarding the net wealth components, inequality is significantly higher in the case of financial wealth than real wealth (Figure 2). Debt also has a very skewed distribution which is driven by the fact that more than 50 per cent of households do not have any debt.

The high inequality in the distribution of the main economic aggregates, in particular of wealth and its components, means the behaviour of these variables is largely determined by a subset of households. The HFCS data enables identifying in which household types these aggregates are concentrated. The remainder of this section describes the distribution of these aggregates by demographic and socioeconomic characteristics of the households. In order to better understand the distributions of real wealth, financial wealth and debt, the analysis will cover both participation rates and

2. Appendix B defines the HFCS variables used in this section.

3. All the statistics presented in this article were calculated using the final sample weights, which means that they are representative of households living in Portugal.

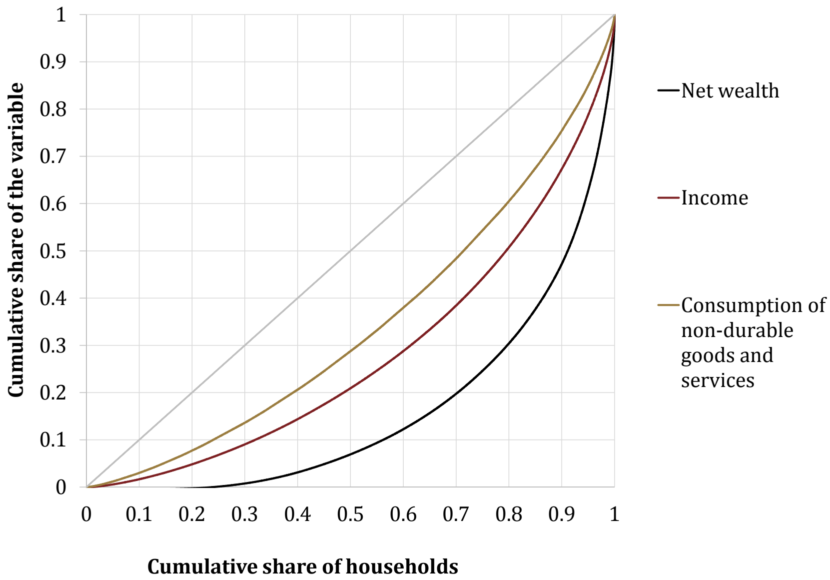

FIGURE 1: Distributions of net wealth, income and consumption: HFCS 2013.

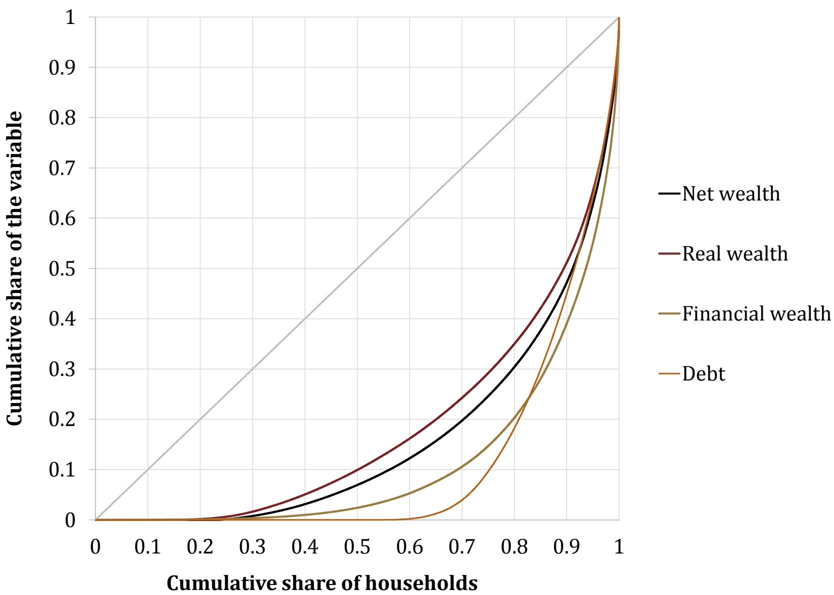

FIGURE 2: Distributions of net wealth and its components: HFCS 2013.

their median values conditional on participation, for the different assets and liabilities. The article focus on median values because they are less sensitive to extreme values than the mean and thus are a better indicator of the typical household. Households will be characterized by their levels of net wealth and income, size, and the age, education level and work status of the reference person. The reference person was selected among the household members in accordance with the definition of Canberra, corresponding roughly to the highest income earner in the household (Appendix B).

Net wealth

The mean net wealth of Portuguese households in the second quarter of 2013 was 156 thousand euros (Table 1). The median was less than half this amount (71.2 thousand euros), illustrating its uneven distribution in the population. For the bottom net wealth quintile (i.e., for the 20 per cent of households with the lowest net wealth), the median value is about 500 euros, while for wealthiest 10 per cent it is more than 600 thousand euros.

In line with the life cycle theory, net wealth increases with the age of the reference person until retirement and falls thereafter. The increase in early life is more pronounced than the reduction in old age. Thus, net wealth is higher for households whose reference person belongs to the highest age classes than for households whose reference person is in the lowest age classes. The fact that older individuals hold wealth to leave as inheritances as well as for precautionary motives (due not only to the macroeconomic uncertainty but also to the uncertainty around the moment of death) might contribute to this age profile of net wealth. The data also shows the usual positive correlation between net wealth and income. Among other factors, this reflects the higher ability to save of households with higher income as well as the increase in income associated with the ownership of assets. As expected, net wealth increases with the education level (which is related to permanent income), more markedly for households whose reference person has tertiary education. By work status, net wealth is highest for households with a self-employed reference persons and lowest for households whose reference person is neither working nor retired. In terms of household size, net wealth reaches a maximum level for households with four members and declines for larger households, although it remains higher than for single-member households. By income, net wealth, work status and education classes there is generally a positive correlation between the levels of net wealth and its components, i.e., the groups of households with the highest net wealth levels are also those with highest levels of real wealth, financial wealth, and debt. In the case of age, the pattern is slightly different mainly because debt levels peaks at younger ages.

	% of households	Net wealth		Annual income		Annual consumption of non-durable goods and services	
		Median	Mean	Median	Mean	Median	Mean
Total	100.0	71.2	156.0	15.4	21.5	8.4	10.0
Income percentile							
<=20	20.0	24.6	70.3	5.6	5.2	4.8	5.1
20-40	20.0	57.6	103.1	10.3	10.4	7.2	7.2
40-60	20.0	71.0	135.1	15.4	15.6	8.9	9.3
60-80	20.0	82.6	158.2	23.4	23.7	10.8	11.4
80-90	10.0	121.8	218.8	35.2	35.8	12.1	13.7
>90	10.0	240.4	408.3	57.9	70.1	18.0	19.9
Age							
<35	11.2	24.1	78.9	16.2	20.6	8.4	9.2
35-44	20.8	63.8	131.6	18.8	23.8	9.6	11.0
45-54	20.1	75.2	162.1	19.0	24.9	9.4	10.9
55-64	18.0	104.2	195.3	16.5	23.9	9.2	10.9
65-74	15.2	92.1	187.6	12.7	18.7	8.4	9.5
>=75	14.7	71.7	160.0	8.7	14.6	6.0	7.1
Work status							
Employee	45.5	62.3	115.9	20.0	25.8	9.6	11.3
Self-employed	10.8	188.2	411.6	22.5	34.6	10.1	11.8
Unemployed	8.3	21.1	86.4	10.0	11.8	6.5	7.4
Retired	31.2	79.8	152.4	11.4	15.4	7.2	8.6
Other not working	4.3	27.9	99.2	5.3	7.8	5.4	6.0
Education							
Lower than secondary	69.4	62.2	131.4	12.7	16.3	7.7	8.3
Secondary	13.7	66.6	144.5	20.1	24.8	9.6	11.2
Tertiary	16.9	131.7	265.7	33.9	40.3	13.2	15.6
Household size							
One	20.0	42.7	120.2	7.6	11.3	5.0	6.1
Two	32.0	78.2	164.6	13.8	19.7	8.4	9.1
Three	24.6	76.9	150.7	19.7	24.3	9.6	11.0
Four	16.3	84.6	180.8	22.2	29.7	11.3	13.3
Five and more	7.1	67.3	178.6	23.9	30.5	12.0	13.5
Net wealth percentile							
<=20	20.0	0.5	-2.0	10.4	12.7	6.4	7.3
20-40	20.0	25.6	26.8	13.9	16.9	7.5	8.4
40-60	20.0	71.3	72.3	14.8	18.3	8.4	9.4
60-80	20.0	139.1	142.6	17.9	24.5	9.6	10.7
80-90	10.0	262.4	267.7	23.6	30.2	11.2	12.8
>90	10.0	629.1	813.9	29.9	40.7	12.0	15.1

TABLE 1. Net wealth, gross income and consumption, by household characteristics: HFCS 2013.

Unit: Thousand, EUR.

Real assets

According to HFCS 2013, real assets account for more than 85 per cent of gross households' wealth (Table 2). The very high share of real wealth is common to all households groups, dropping only slightly with income and education levels.

	Share of total assets		Share of real assets					Share of financial assets				
	Real assets	Financial assets	Main residence	Other real estate properties	Self-employment business	Vehicles	Valuables	Sight accounts	Saving accounts	Tradable assets	Voluntary pensions schemes	Other
Total	88.0	12.0	49.8	29.9	15.4	3.7	1.3	10.8	56.0	6.9	12.7	13.6
Income percentile												
<=20	90.5	9.5	59.0	35.2	3.3	2.1	0.4	17.3	60.8	3.2	5.4	13.3
20-40	88.5	11.5	55.0	36.0	5.1	2.8	1.0	10.6	66.3	2.1	7.3	13.8
40-60	89.0	11.0	52.9	31.8	10.9	3.6	0.9	11.3	55.2	5.0	14.1	14.4
60-80	88.9	11.1	51.4	28.1	15.1	4.2	1.2	12.3	61.6	4.0	12.3	9.8
80-90	88.3	11.7	49.1	23.7	21.9	4.4	0.9	11.5	50.6	5.1	17.2	15.6
>90	85.4	14.6	41.2	28.8	23.8	4.0	2.2	8.1	50.7	13.0	13.5	14.5
Age												
<35	89.4	10.6	55.2	22.8	14.9	6.1	0.9	16.0	53.4	10.2	14.8	5.6
35-44	90.2	9.8	54.7	16.3	23.7	4.6	0.8	12.1	53.7	5.7	20.6	7.9
45-54	87.5	12.5	52.6	24.7	16.9	4.3	1.5	9.0	43.2	6.7	17.5	23.6
55-64	87.3	12.7	48.3	30.4	15.6	3.8	1.9	9.9	49.9	8.9	13.3	18.0
65-74	87.1	12.9	45.1	40.3	11.1	2.6	0.9	11.4	68.5	5.5	5.5	9.2
>=75	86.2	13.8	41.4	53.1	3.3	1.0	1.1	10.3	74.0	5.8	2.1	7.7
Work status												
Employee	87.9	12.1	63.5	22.8	6.6	5.5	1.7	12.1	53.7	6.9	17.9	9.3
Self-employed	90.1	9.9	28.2	24.8	43.7	2.6	0.8	8.0	38.4	7.7	15.8	30.1
Unemployed	90.2	9.8	57.0	32.8	4.3	4.1	1.8	13.7	50.0	4.9	10.5	20.9
Retired	85.6	14.4	50.6	44.1	1.9	2.4	1.0	10.8	72.8	6.2	4.9	5.3
Other not working	87.3	12.7	50.0	47.1	-0.3	1.9	1.4	11.7	48.4	11.0	1.0	28.0
Education												
Lower than secondary	89.1	10.9	49.2	34.9	11.8	3.3	0.9	11.8	61.5	3.4	11.2	12.1
Secondary	88.7	11.3	57.7	19.2	17.6	4.7	0.9	11.4	49.9	11.0	15.0	12.8
Tertiary	85.5	14.5	47.2	25.6	21.0	4.1	2.1	9.4	50.8	10.2	13.8	15.9
Household size												
One	88.9	11.1	42.5	40.9	13.6	1.8	1.3	12.3	62.8	7.0	9.1	8.8
Two	87.5	12.5	48.2	35.2	12.5	3.2	0.9	11.9	65.4	6.3	8.1	8.2
Three	87.8	12.2	54.0	23.5	16.3	4.8	1.5	10.6	52.3	5.7	15.2	16.2
Four	88.4	11.6	54.1	20.9	19.0	4.4	1.5	9.1	48.0	9.3	19.4	14.3
Five and more	87.7	12.3	45.4	31.7	17.2	4.6	1.2	9.0	39.4	7.1	12.4	32.1
Net wealth percentile												
<=20	92.0	8.0	75.3	13.7	-0.2	10.9	0.3	47.7	27.6	1.3	10.2	13.2
20-40	89.4	10.6	82.5	5.2	4.2	7.6	0.6	22.4	57.2	1.2	10.0	9.2
40-60	87.6	12.4	83.7	8.4	1.3	5.8	0.8	17.8	62.2	3.8	9.8	6.5
60-80	85.9	14.1	75.8	13.2	4.6	5.1	1.3	11.3	65.0	3.2	13.6	6.8
80-90	85.3	14.7	59.4	27.5	8.1	3.9	1.1	9.0	63.0	6.3	16.1	5.7
>90	89.4	10.6	22.9	46.4	27.4	1.8	1.5	6.5	47.0	11.1	11.8	23.6

TABLE 2. Gross wealth composition, by asset type and household characteristics: HFCS 2013.

Unit: Per cent

The main residence is the most important asset held by households, with a share of around 50 per cent of total real wealth. Other real estate properties are the second most important real asset, having a share of about 30 per cent in real wealth. Self-employment businesses represent about 15 per cent and motor vehicles about 4 per cent.

The overriding importance of the main residence in wealth is common to most household types. However, its share on real assets declines with income, age as well as for the highest net wealth classes. The share of the other real estate properties is more heterogeneous across different household types, increasing with age and also in households with higher net wealth levels. For households in the highest class of net wealth this is the most important asset, followed by self-employment businesses. By age, the importance of businesses is higher for households whose reference person is younger, declining particularly after retirement. As expected, by work status, businesses are more important for households with self-employed reference persons.

Around 75 per cent of Portuguese households own their main residence, around 30 per cent are owners of other real estate properties, and around 13 per cent are owners of self-employment businesses (Table 3). The median values of these assets for the households that own them are 90 thousand euros, 60 thousand euros and 50 thousand euros, respectively. Motor vehicles are the second most common real asset, held by more than 70 per cent of the households, but its median value is only 5 thousand euros. In Portugal, participation in real estate properties is higher, but its weight on the real wealth is similar, when compared to the euro area.

By household groups, the participation rates and the median values of the different real assets generally follow a pattern similar to the evolution of the total wealth, i.e., increase with income and net wealth and achieve higher values for households whose reference person has an higher level of education or is self-employed. By age, the percentage of homeowners reaches its highest value already by the second youngest age group, while participation in other real estate properties increases until after retirement. The median value of the main residence decreases with the age of the reference person, probably reflecting the fact that younger households own more recently constructed, higher value properties.

	Participation in assets (in %)						Median value of assets conditional on participation (thousand, EUR)					
	Any real asset	Main residence	Other real estate properties	Self-employment business	Vehicles	Valuables	All real assets	Main residence	Other real estate properties	Self-employment business	Vehicles	Valuables
Total	90.0	74.7	30.3	12.7	73.3	9.6	101.9	91.3	62.2	49.0	5.0	5.0
Income percentile												
<=20	74.0	60.6	19.8	3.2	39.2	4.0	52.2	51.1	19.7	5.8	1.5	1.0
20-40	86.8	66.8	26.6	7.0	64.8	6.9	70.9	70.9	25.8	12.7	2.0	1.4
40-60	93.7	76.1	28.8	11.8	80.3	8.9	97.0	88.0	63.2	19.4	4.0	2.8
60-80	96.3	78.7	30.1	13.4	89.2	11.1	112.4	100.0	73.5	28.0	5.5	4.8
80-90	99.1	89.0	38.4	25.2	92.7	11.6	162.5	120.0	80.9	77.2	9.2	6.1
>90	99.2	93.7	54.5	30.7	93.2	22.6	268.4	151.0	121.0	127.1	15.0	14.0
Age												
<35	84.3	54.9	16.0	11.0	78.7	7.5	97.8	107.5	58.2	54.1	5.2	2.8
35-44	94.8	79.7	22.8	16.8	86.5	7.5	115.0	100.0	71.0	57.8	6.1	5.0
45-54	90.6	76.1	30.3	17.0	80.3	11.4	107.1	98.7	51.4	27.5	5.5	5.5
55-64	91.3	78.8	34.4	14.9	78.8	11.2	110.7	98.0	75.9	65.5	5.0	6.4
65-74	91.2	79.2	41.9	9.0	67.5	9.7	90.2	75.0	62.3	43.8	3.0	3.1
>=75	83.8	71.2	35.0	3.2	40.0	9.7	73.0	62.4	52.0	5.0	1.5	4.7
Work status												
Employee	93.1	76.0	24.6	7.4	85.0	9.4	105.2	100.0	60.0	23.0	6.0	5.0
Self-employed	98.9	84.3	51.5	78.0	88.8	12.0	221.4	113.5	96.1	53.0	7.5	9.3
Unemployed	75.4	54.3	14.0	2.6	63.6	7.7	74.7	87.3	59.0	69.5	4.1	2.5
Retired	88.0	76.7	36.4	2.0	58.8	10.4	83.7	70.2	52.3	29.8	2.5	3.6
Other not working	77.3	61.7	24.6	1.1	33.4	3.0	59.5	54.9	68.8	5.0	1.5	28.9
Education												
Lower than secondary	87.9	71.9	29.8	10.8	67.4	7.9	85.0	76.8	50.0	46.2	3.9	3.0
Secondary	91.5	77.5	24.0	14.2	84.2	9.3	117.2	102.3	68.0	50.0	6.1	3.9
Tertiary	97.5	84.1	37.5	18.9	88.6	17.0	174.5	138.5	117.0	54.0	10.0	10.0
Household size												
One	79.0	62.9	25.8	4.2	39.3	8.4	71.8	66.9	66.4	17.0	2.5	2.5
Two	91.5	77.0	34.0	10.8	74.1	8.5	100.0	83.3	50.0	29.5	3.0	5.0
Three	94.6	77.6	30.2	14.3	89.0	10.9	110.0	99.9	60.0	41.2	5.2	4.1
Four	94.8	83.2	28.4	21.2	87.0	12.4	130.5	106.2	75.0	64.1	7.3	5.8
Five and more	87.3	67.9	31.2	19.8	79.4	7.0	118.8	100.0	93.5	47.8	6.0	18.0
Net wealth percentile												
<=20	55.3	18.9	3.6	3.0	47.0	2.9	3.4	70.0	73.0	0.0	2.0	0.8
20-40	95.2	75.4	15.7	5.8	70.1	5.7	39.6	50.0	8.3	4.7	4.9	1.8
40-60	99.5	91.0	24.0	7.7	76.1	8.2	75.3	70.9	17.7	5.1	4.4	1.2
60-80	100.0	95.5	37.5	13.1	85.9	12.3	133.7	100.3	46.9	21.8	5.9	4.8
80-90	100.0	93.6	59.5	22.5	88.7	14.5	248.9	150.0	103.5	58.1	8.3	6.5
>90	100.0	92.0	82.1	45.0	86.0	23.6	610.1	162.0	320.1	319.3	10.2	21.2

TABLE 3. Real assets participation and median values, by asset type and household characteristics: HFCS 2013.

Financial assets

Deposits are the most important financial asset (Table 2). Sight and saving deposits account, respectively, for around 11 per cent and 56 per cent of total financial wealth. Tradable assets (quoted shares, debt securities and mutual funds) represent about 7 per cent, voluntary pensions about 13 per cent, and other financial assets about 14 per cent.[4] Compared with the euro area, deposits represent a much higher share of financial wealth of households in Portugal.

Saving deposits are the most important asset in the financial wealth for all kinds of households, except those that are in the lowest net wealth class, for which sight deposits have a dominant weight. The share of total deposits is higher for lower income and net wealth classes and for households with older and lower educated reference persons. As expected, tradable assets, which typically are associated with a higher risk and are more sophisticated financially, represent a lower share of these households' financial wealth. By net wealth classes, the share of tradable assets increases from around 1 per cent in the case of the poorest households to around 10 per cent for the wealthiest ones. The importance of voluntary pensions is higher for households in intermediate classes of income and net wealth and for those whose reference person is younger than retirement age or have completed at least secondary education.

As expected, after sight deposits (held by 96 per cent of households), saving deposits are the most frequent type of financial asset, owned by about 50 per cent of the households (Table 4). Around 17 per cent of the households have voluntary pension plans and only 8 per cent hold tradable assets. Saving deposits are the financial asset with the highest median value (about 11 thousand euros). The median values of tradable assets, voluntary pension or other assets are around 5 thousand euros. The median value of sight deposits is 1 thousand euros.

4. The other financial assets mainly include unquoted shares of corporations in which the household members have a role solely as investors and money owed to the household (Appendix B).

	Participation in assets (in %)						Median value of assets conditional on participation (thousand, EUR)					
	Any financial asset	Sight accounts	Saving accounts	Tradable assets	Voluntary pensions schemes	Other	All financial assets	Sight accounts	Saving accounts	Tradable assets	Voluntary pensions schemes	Other
Total	96.3	95.6	48.3	8.1	17.2	10.5	5.1	1.0	11.1	4.9	4.9	5.0
Income percentile												
<=20	88.0	87.0	26.5	1.3	4.4	6.5	1.1	0.5	10.0	8.5	2.4	3.9
20-40	96.7	95.2	42.9	1.3	7.8	7.9	2.4	0.6	10.0	1.4	2.8	2.8
40-60	97.9	97.5	46.9	5.8	14.3	11.7	4.3	0.9	10.0	3.3	3.4	4.4
60-80	99.1	98.5	55.8	8.6	22.8	10.9	6.7	1.2	10.4	2.3	3.2	4.7
80-90	99.6	99.6	65.6	13.7	31.3	13.4	12.7	1.9	10.2	4.5	4.2	8.1
>90	100.0	100.0	73.5	33.4	42.1	18.2	32.0	3.0	24.7	6.4	9.9	8.6
Age												
<35	97.2	97.1	45.1	7.0	22.4	9.2	2.5	0.7	5.0	10.0	1.8	2.3
35-44	98.7	98.5	52.9	10.2	27.2	13.5	5.0	0.9	7.7	2.3	3.4	4.0
45-54	97.4	97.0	43.5	8.1	20.7	12.4	4.7	1.0	12.0	5.5	5.0	4.9
55-64	96.6	96.2	47.7	9.8	17.7	11.3	6.4	1.0	14.9	5.1	9.0	9.1
65-74	96.6	95.1	50.9	7.2	8.6	7.5	6.0	1.2	17.8	5.0	6.0	7.4
>=75	90.0	88.3	48.8	4.7	2.5	6.9	6.8	1.0	19.9	2.4	13.8	5.8
Work status												
Employee	99.1	98.8	50.5	9.6	24.8	11.2	4.8	1.0	9.9	4.0	3.4	3.0
Self-employed	98.4	98.3	51.3	12.3	24.2	19.7	10.6	2.0	14.5	5.3	10.0	14.6
Unemployed	91.6	91.0	30.4	3.4	10.3	11.0	1.2	0.4	6.1	5.5	4.2	4.0
Retired	94.4	92.9	51.4	6.3	7.5	7.0	6.8	1.1	16.6	3.7	6.0	5.6
Other not working	84.2	83.6	29.6	3.8	2.6	5.8	1.3	0.5	9.8	28.2	5.0	40.6
Education												
Lower than secondary	94.9	94.1	42.7	4.3	10.6	9.1	3.3	0.8	10.4	4.6	4.4	4.8
Secondary	98.9	98.0	53.7	10.3	25.9	12.7	6.6	1.0	10.0	4.2	3.1	4.0
Tertiary	99.8	99.8	66.9	21.8	36.9	14.8	16.8	2.0	15.5	5.0	6.0	5.0
Household size												
One	92.0	91.0	39.1	5.0	10.3	7.6	2.9	0.7	10.8	2.2	4.6	4.4
Two	96.9	95.9	50.9	7.1	14.5	9.5	6.8	1.0	14.6	3.1	3.4	3.1
Three	98.0	97.8	52.3	9.7	22.2	12.5	5.8	1.0	10.0	5.0	4.6	5.0
Four	98.3	97.9	50.6	10.9	22.6	12.4	5.2	1.0	9.9	3.4	7.7	6.2
Five and more	95.2	94.4	43.8	9.4	18.7	12.4	3.9	0.9	14.0	6.9	6.7	9.1
Net wealth percentile												
<=20	90.1	89.6	15.6	1.3	5.2	4.3	0.4	0.3	2.0	0.5	1.2	1.0
20-40	95.2	93.9	42.5	3.0	14.6	9.6	3.1	0.8	6.0	0.7	2.3	3.3
40-60	97.7	97.3	52.7	5.3	15.5	9.5	6.0	1.0	9.8	4.6	3.7	3.8
60-80	99.4	98.6	61.2	8.7	20.4	11.3	12.0	1.5	17.9	4.3	5.6	5.0
80-90	99.2	99.2	68.2	17.5	29.6	14.0	26.1	2.0	25.3	5.0	8.9	5.1
>90	99.2	98.1	70.9	26.9	30.9	22.0	40.7	3.0	30.9	7.2	14.6	15.0

TABLE 4. Financial assets participation and median values, by asset type and household characteristics: HFCS 2013.

Similarly to the real assets, both participation rates and conditional median values of the financial assets in general increase with the level of net wealth and income. In most cases, participation rates are highest when the reference person is 35-44 years old. However, these households are not the ones with the highest median values. While for deposits the median value increases with age, for tradable assets it reaches the highest level in households with younger reference persons and in the cases of voluntary pensions and other financial assets in the age group prior to retirement. This behaviour of the other financial assets is to a large extent determined by the money owed to the household. As referred in Appendix A, the HFCS 2013 includes information about the part of this money that is owed by businesses owned by any household member. This type of asset represents about 4 per cent of total financial wealth, but makes up 12 per cent on the financial wealth of households who owned businesses.

Debt

Mortgages on the main residence represent slightly more than 80 per cent of total household debt (Table 5). The dominant weight of mortgages is common to all household groups. Nevertheless, for households with older, self-employed or retired reference persons mortgage debt is slightly less important than for the remaining households. The share of the mortgages on other real estate properties is more heterogeneous across households, in line with what happens with the ownership of these properties. This type of mortgages is more important for households with higher levels of income and net wealth and for those with self-employed reference persons. Non-mortgage debt has a higher share on the debt when the reference person has a lower education level, is not working nor unemployed, or is older. While the share of non-mortgage loans is higher for lower-income households, in the case of credit cards, credit lines and bank overdrafts, there appears to be no relationship with income.

About 45 per cent of Portuguese households had some type of debt in the second quarter of 2013, with a median of 48.5 thousand euros (Table 6). The percentage of indebted households in Portugal is identical to that in the euro area, but the median value of debt is higher, reflecting the higher participation in mortgages.

	HMR mortgage	Other property mortgages	Non-mortgage loans	Credit lines, overdrafts and credit cards
Total	82.4	10.6	6.2	0.8
Income percentile				
<=20	86.3	6.2	6.7	0.8
20-40	84.8	1.6	12.6	1.1
40-60	83.1	7.6	8.4	0.9
60-80	84.5	8.5	6.4	0.6
80-90	86.8	8.5	4.2	0.6
>90	75.6	19.1	4.4	0.9
Age				
<35	81.2	14.3	3.9	0.6
35-44	85.7	9.6	4.4	0.3
45-54	82.9	10.5	5.7	0.8
55-64	78.4	7.4	11.7	2.6
65-74	53.3	10.9	33.9	2.0
>=75	37.2	22.8	31.6	8.5
Work status				
Employee	87.3	7.7	4.5	0.5
Self-employed	67.7	23.0	7.8	1.5
Unemployed	82.0	8.4	8.3	1.3
Retired	66.0	9.1	23.3	1.7
Other not working	79.0	0.1	19.6	1.3
Education				
Lower than secondary	81.9	7.3	9.8	1.1
Secondary	87.4	7.6	4.6	0.5
Tertiary	80.1	15.5	3.7	0.7
Household size				
One	85.6	5.3	7.2	1.8
Two	77.6	15.1	6.3	1.0
Three	82.6	9.8	7.0	0.7
Four	85.3	9.9	4.3	0.4
Five and more	80.7	10.6	7.7	0.9
Net wealth percentile				
<=20	75.1	9.0	14.8	1.1
20-40	86.3	9.7	3.4	0.6
40-60	90.5	5.1	4.1	0.3
60-80	84.3	9.8	5.3	0.6
80-90	81.1	15.1	3.4	0.5
>90	69.6	20.0	8.5	1.9

TABLE 5. Debt composition, by debt type and household characteristics: HFCS 2013. Unit: Per cent

	Participation in debt (in %)					Median value of the outstanding debt conditional on participation (thousand, EUR)				
	Any debt	HMR mortgage	Other property mortgages	Non-mortgage loans	Credit lines, overdrafts and credit cards	All debt	HMR mortgage	Other property mortgages	Non-mortgage loans	Credit lines, overdrafts and credit cards
Total	45.9	32.7	3.7	17.3	8.8	48.5	63.7	58.8	4.0	0.7
Income percentile										
<=20	21.6	11.1	0.6	10.8	4.1	9.9	41.9	43.3	1.6	0.5
20-40	30.4	16.8	0.3	14.8	6.0	12.2	39.5	54.0	3.0	0.5
40-60	49.4	35.1	3.4	19.8	9.0	45.6	58.7	37.3	5.3	0.8
60-80	58.8	42.6	5.2	22.0	12.3	53.6	65.1	62.8	4.3	0.6
80-90	69.1	57.3	6.5	20.1	13.3	73.6	80.4	70.2	5.0	0.7
>90	69.4	58.4	11.2	18.2	11.7	80.4	86.8	70.2	8.7	1.1
Age										
<35	65.1	45.0	2.8	25.7	12.4	76.8	89.9	83.4	3.8	0.5
35-44	75.5	61.6	7.7	25.8	11.8	68.7	72.8	65.0	5.6	0.5
45-54	60.2	44.3	4.8	20.9	11.8	39.3	49.5	61.1	3.8	0.8
55-64	41.4	26.1	2.6	17.1	9.1	19.7	35.1	32.3	3.6	0.8
65-74	17.1	7.1	1.9	8.7	4.1	9.1	24.6	27.8	7.0	1.0
>=75	4.9	0.8	0.2	3.1	2.0	4.2	32.0	151.2	3.0	2.1
Work status										
Employee	67.6	52.7	5.0	23.8	12.0	56.5	68.3	63.0	4.3	0.5
Self-employed	55.8	40.0	8.3	18.7	11.1	59.6	72.4	62.6	9.7	1.5
Unemployed	45.3	22.2	2.0	23.2	9.8	12.4	60.5	54.6	1.6	0.5
Retired	15.5	7.4	1.1	6.9	4.0	8.9	21.1	18.7	3.3	0.9
Other not working	11.6	5.3	0.0	8.8	1.0	10.8	52.7	0.0	2.9	0.8
Education										
Lower than secondary	36.1	22.6	2.2	16.5	6.8	25.3	48.0	31.8	3.7	0.6
Secondary	68.8	55.0	5.2	21.7	15.8	60.6	69.2	63.6	5.0	0.7
Tertiary	67.3	55.8	8.4	16.9	11.2	84.7	89.9	74.3	5.7	0.7
Household size										
One	26.3	35.4	1.2	10.4	8.2	31.0	59.9	28.0	3.0	0.5
Two	32.8	32.6	1.9	12.3	6.7	35.4	56.0	43.1	3.6	0.5
Three	58.9	37.2	5.4	21.9	10.1	54.4	66.6	63.0	6.9	1.0
Four	70.1	16.8	6.9	24.4	10.0	56.6	65.0	53.6	4.2	0.8
Five and more	59.4	460.1	5.1	26.8	12.6	49.2	69.2	83.7	5.0	0.5
Net wealth percentile										
<=20	37.7	15.8	1.8	24.4	9.6	20.2	85.1	90.0	3.4	0.6
20-40	54.0	43.3	3.0	17.6	11.7	62.3	70.9	66.4	3.9	0.6
40-60	50.0	40.5	2.6	16.9	7.1	42.4	49.3	50.4	3.0	0.6
60-80	43.3	33.1	2.3	14.6	7.3	40.7	55.2	51.0	6.4	0.6
80-90	44.6	31.9	7.8	12.5	8.5	43.5	57.2	44.7	4.2	0.8
>90	44.3	29.5	9.4	13.5	7.9	62.0	74.4	50.4	11.3	2.4

TABLE 6. Debt participation and median values, by debt type and household characteristics: HFCS 2013.

The percentage of indebted households and the median amount of debt increases with income and is higher for households whose reference person is working, younger than 45 years old, or has a higher level of education. This behaviour is largely determined by mortgages. Participation in non-mortgage debt is also higher in young age groups. Its value does not seem to change monotonically with age, in the case of non-mortgage loans, and increases with age, in the case of credit cards, credit lines and bank overdrafts. By income, participation in non-mortgage debt reaches the maximum level in the intermediate classes, although the median value increases with income, as in the case of mortgages. By work status, the incidence of non-mortgage debt is higher not only in households whose reference person is working, as in the case of mortgages, but also in the case of unemployment. The median value of non-mortgage debt is higher in households with self-employed reference persons.

Income

In 2012, according to HFCS 2013, the annual mean and median gross income of the Portuguese households were, respectively, 21.5 thousand euros and 15.4 thousand euros (Table 1). In the 20 per cent of households with the lowest incomes, the median was lower than 6 thousand euros, and in the 10 per cent households with the highest incomes was around 58 thousand.

Income increases with the age of the reference person until the 45-54 age group, and subsequently declines. Contrary to what happens to the net wealth, income is higher in lowest age group than in the highest group. This result holds when one takes into account the household composition, i.e., when measuring the income per equivalent adult. As expected, household income increases with the education level of the reference person and is higher when the reference person is working and in particular when they are self-employed.

In aggregate terms, income from employment is the main source of income (representing around 70 per cent of the total households income), and particularly income earned by employees (around 55 per cent of the total). The second main source of income is public pensions (around 20 per cent of the total). The share of the different income sources changes with the households' financial situation. The income earned by employees is slightly more important for households in the three lowest wealth classes than in the three highest (Figure 3). By contrast, the share of self-employment income is higher for the wealthy households. In these households, income from real estate, financial assets, and businesses also have a significantly higher weight.

The HFCS includes some qualitative questions for assessing whether households had some negative shocks to their income or labour market situation in the years preceding the interview. According to the HFCS, in 2013 about 45 per cent of the households considered that the previous

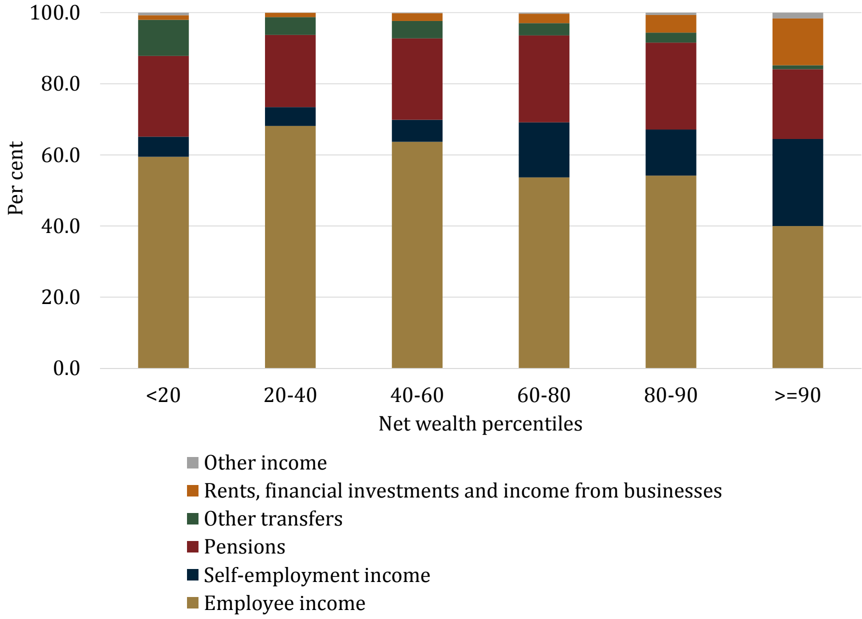

FIGURE 3: Income composition: HFCS 2013.

year income was lower than in a normal year. This percentage is above 50 per cent in the highest income classes, as well as in households whose reference person is unemployed, self-employed, has an intermediate age, or a higher level of education. Among the reference persons that have worked (at least at some point in time) in the three years prior to the HFCS 2013, the percentage that declared to have had a reduction in labour income increases with income, while the percentage declaring to have lost the job declines with income (Figure 4). This data suggests, that in the three years preceding the survey, lower income households were relatively more affected by rising unemployment and higher income households by reductions in labour income.[5]

Consumption

Data on consumption is less comprehensive than in the cases of wealth and income and is collected in a more aggregated way, focusing on the

5. The percentage of households whose reference person declared to have lost the job also declines with the education level. This suggests the higher incidence of job loss situations at lower income percentiles is not being determined by a movement to lower income percentiles of the households whose reference person have lost the job.

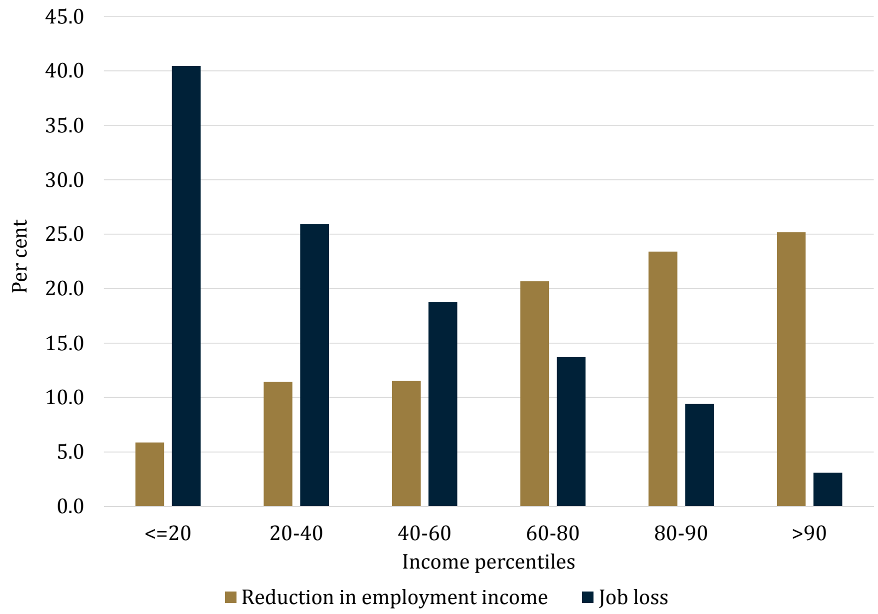

FIGURE 4: Unfavourable evolution of job conditions: HFCS 2013.

Note: Percentage of households whose reference person has lost the job or had a reduction of labour income in the 3 years prior to the HFCS 2013, among the total number of households in which the reference person has worked at some point during this period.

consumption of non-durable goods and services.[6] According to the HFCS 2013, the mean value of the regular annual expenditures on non-durable goods and services is 10 thousand euros and the median 8.4 thousand euros (Table 1).

The mean and median values of consumption increase with net wealth, the level of education, and more significantly with income. By work status, consumption reaches the highest values in households whose reference person is working and by age in the 35-44 years old group. The consumption per equivalent adult has a similar pattern, although with a smaller dispersion by household type. Additionally, by age it reaches the maximum value in the class of 55-64 years old. The consumption items collected in HFCS vary by type of household in an identical fashion to the total consumption. Nevertheless, the share of both food at home and of utilities declines with income, while the share of food outside home and of the other expenses in non-durable goods and services increases (Figure 5).

6. The HFCS does not provide an estimate of consumption as accurate as that obtained in the household expenditure surveys, where this is collected in a far more disaggregated way.

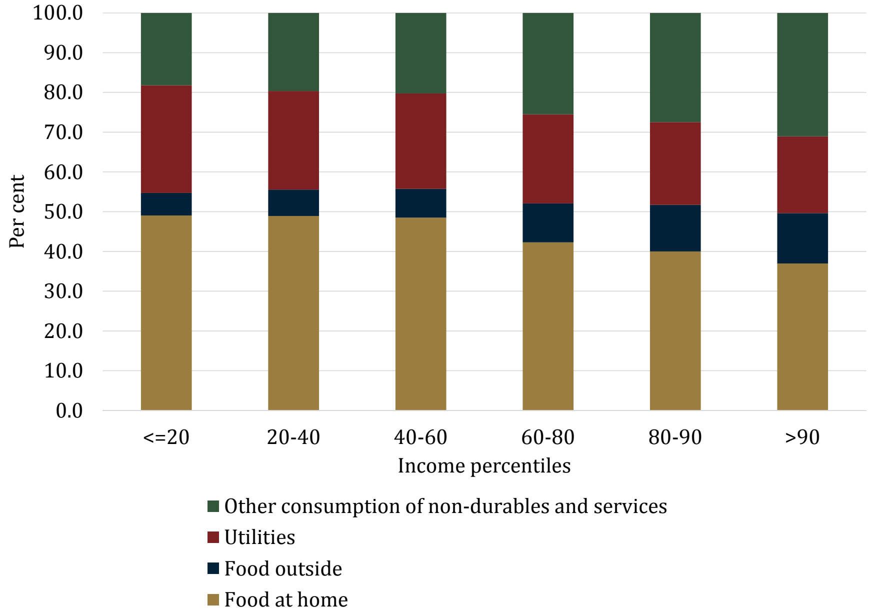

FIGURE 5: Composition of consumption: HFCS 2013.

Macroeconomic developments in the period 2010-13

In the remaining sections of the article the results of HFCS 2013 will be compared to the ones of the HFCS 2010. Prior to this analysis it is important to briefly describe the macroeconomic framework of the Portuguese economy in the period between the first two waves of HFCS.

Throughout 2010 and early 2011, Portugal was severely hit by the increase in risk aversion associated with the European sovereign debt crisis. The conditions of access to the international financial markets deteriorated significantly and the country requested an Economic and Financial Assistance Programme in May 2011, which ended in June 2014. This programme involved the implementation of a series of measures to correct the imbalances prevailing in the balance sheets of the private and public sectors and the removal of some roadblocks to potential growth. Many of the economic measures implemented in the period between the two survey waves had a direct negative impact on the financial situation of households, involving, for example, income reductions for public servants and retirees, increases in income and consumption taxes, and reduction in unemployment benefits.

During this period the Portuguese economy went through a deep recession linked to a downward adjustment of domestic demand. In a context of declining disposable income, increasing unemployment, and a sharp drop in consumer confidence, private consumption fell significantly and the household saving rate broke from the downward trend registered since the beginning of euro area (Banco de Portugal (2016)).

The increased risk perception, in a context where banks faced financing difficulties and the need to restructure their balance sheets, has also resulted in a deterioration of household financing conditions. Interest rate spreads on new bank loans increased significantly and the total value of new loans declined.

Indebted households, especially those with mortgages, however benefited from the reduction in Euribor interest rates in a context of the accommodative monetary policy implemented by the ECB. Finally, the financial situation of households has also been affected by the reduction in the real estate prices and of higher risk financial assets.

Changes in the distribution of net wealth in the period 2010-13

This section compares the main results obtained in the HFCS 2013 and in HFCS 2010.[7] In order for this analysis to be conducted in real terms, the HFCS 2010 data has been adjusted by inflation.[8]

The comparison of the results between the two waves should be performed and interpreted with caution. First, when comparing results for groups of households it is important to note the existence of composition effects. Groups' composition changes over time and these changes may have been particularly pronounced in the period under analysis, given the macroeconomic developments mentioned in the previous section. For example, the change in the income of households whose reference person is unemployed reflects the evolution of the income of households whose reference person was unemployed in 2010 and still unemployed in 2013, as well as the change in the type of households with unemployed reference persons. Secondly, it is important to take into account the uncertainty surrounding the production of the survey data. Thus in the comparisons of the main results the standard errors of the statistics are taken into account and a greater focus is given to cases where the equality of the values obtained with the two waves of the survey is statistically rejected.[9]

7. The data of the first wave differs slightly from the one previously released due to a revision of weights incorporating more updated information (Appendix A).

8. All HFCS 2010 values have been increased by 7.9 percent, which corresponds to the change in the consumer prices in the period 2009-12, i.e., between the reference periods for income. The inflation in the period from the second quarter of 2010 to the second quarter of 2013, i.e. between the reference periods for assets and liabilities, is very close to this value.

9. The standard errors take into account uncertainty due to the sampling and to the imputation process. As explained in the Annex 1 of Costa and Farinha (2012b) the standard errors were calculated using the five implicates as well as the one thousand replicate weights which are part of HFCS database.

	Median		Mean	
	HFCS 2010	HFCS 2013	HFCS 2010	HFCS 2013
Net wealth	85.0	71.2***	170.4	156
	(3.2)	(2.4)	(8.9)	(5.7)
Gross wealth	114.3	103.9***	203.0	184.8*
	(2.7)	(2.3)	(8.9)	(5.7)
Real wealth	103.9	90.8***	179.5	162.5*
	(3.2)	(2.3)	(7.9)	(5.3)
Financial wealth	4.4	4.5	23.5	22.2
	(0.3)	(0.4)	(1.5)	(0.9)
Debt	0.0	0.0	32.6	28.8***
	-	-	(0.3)	(0.2)
Income	16.6	15.4***	23.3	21.5**
	(0.4)	(0.2)	(0.5)	(0.5)

TABLE 7. Main aggregates: HFCS 2010 vs HFCS 2013.

Unit: Thousand, EUR.

Notes: The HFCS 2010 values are adjusted by the consumer prices changes between the two waves of the survey. The values in parenthesis are the standard errors. ***, ** and * indicate that the test on the equality of the HFCS 2010 and HFCS 2013 statistics is rejected at 1 per cent, 5 per cent and 10 per cent, respectively.

According to HFCS, the median net wealth of Portuguese households had a reduction in real terms in the period between the second quarter of 2010 and the second quarter of 2013 (Table 7). The decline is not statistically significant for the mean. In fact, the decline in the mean real wealth seems to have been compensated by the decline in debt, in a context of no significant changes on financial wealth. The mean and median values of income declined in real terms between the two waves. Overall, these developments are in line with the macroeconomic data available for income, financial wealth and debt. The National Accounts do not provide data for non-financial assets but the reduction in real estate prices and in housing investment observed during this period suggests a decline in real wealth in line with HFCS data.

The median net wealth fell for households' classes with net wealth lower than the 80th percentile, remained relatively stable for households with net wealth between the 80th and 90th percentiles and increased for the wealthiest 10 per cent households (Table 8).[10] This developments suggest an increase in net wealth inequality in the period between the two waves. The share of net wealth held by the half households with lower net wealth, decreased from 8.7 per cent to 7.1 per cent, while for the wealthiest 10 per cent increased from 51.6

10. These results are robust to the exclusion of the households that belong to the sub-sample that intends to oversample the wealthiest households and thus are not being determined by the change in the oversampling method described in Appendix A.

	Median		Mean	
	HFCS 2010	HFCS 2013	HFCS 2010	HFCS 2013
Net wealth percentile				
<=20	1.7	0.5***	1.4	-2***
	(0.4)	(0.1)	(0.8)	(0.7)
20-40	37.7	25.6***	36.7	26.8***
	(3.4)	(1.7)	(2.4)	(1.7)
40-60	85.0	71.3***	85.2	72.3***
	(3.2)	(2.4)	(3.2)	(2.4)
60-80	155.5	139.1**	158.0	142.6**
	(6.1)	(4.5)	(5.2)	(4.1)
80-90	260.9	262.4	265.3	267.7
	(10.8)	(9.8)	(9.1)	(10.7)
>90	545.9	629.1*	878.1	813.9
	(40.6)	(29.6)	(76.8)	(43.7)

TABLE 8. Net wealth: HFCS 2010 vs HFCS 2013.

Unit: Thousand, EUR.

Notes: The HFCS 2010 values are adjusted by the consumer prices changes between the two waves of the survey. The values in parenthesis are the standard errors. ***, ** and * indicate that the test on the equality of the HFCS 2010 and HFCS 2013 statistics is rejected at 1 per cent, 5 per cent and 10 per cent, respectively.

per cent to 52.1 per cent. In line with this evolution, the Gini index increased slightly from 66 per cent, to 67.8 per cent.

This moderate increase in net wealth inequality mainly reflects the evolution of real wealth and debt (Table 9). For households owning real assets, the median real wealth declined for the households with net wealth lower than the 80th percentile and this decline is statistically significant between the 20th and 80th percentiles. In the case of debt, while in the three lowest net wealth classes participation remained constant or increased, in the three highest there was a significant reduction in the percentage of households with debts. In addition, although the median values of debt declined for all net wealth classes, these reductions are not statistically significant for households with net wealth lower than the 60th percentile. For financial wealth, the only significant change is a decline in the median value for the 20 per cent poorest households.

The decline in the aggregate real wealth was determined by a slight reduction in participation and mainly by a decrease in the value of these assets. In the case of financial wealth, participation increased slightly but the median value did not changed significantly. Regarding debt, the aggregate reduction stems mainly from a decrease in debt values. The percentage of indebted households has remained relatively stable at around 46 per cent.

	Real assets		Financial assets		Debt	
	HFCS 2010	HFCS 2013	HFCS 2010	HFCS 2013	HFCS 2010	HFCS 2013
	Participation in assets or debt (%)					
Net wealth percentile						
<=20	61.1	55.3	88.1	90.1	34.3	37.7
	(2.2)	(2.7)	(1.5)	(1.5)	(2.6)	(2.5)
20-40	97.3	95.2	94.8	95.2	45.7	54**
	(1)	(1.1)	(1.1)	(1)	(2.7)	(2.2)
40-60	99.5	99.5	95.1	97.7*	47.4	50
	(0.5)	(0.5)	(1.3)	(0.8)	(2.9)	(2.4)
60-80	99.8	100	97.8	99.4	50.0	43.3*
	(0.4)	(0.3)	(1.1)	(0.5)	(3)	(2.1)
80-90	100.0	100	98.8	99.2	55.9	44.6**
	(1)	(0.6)	(1.3)	(0.9)	(3.9)	(3.5)
>90	100.0	100	99.6	99.2	51.6	44.3*
	(0.8)	(0.4)	(0.9)	(0.7)	(3.3)	(2.7)
Total	91.5	90*	95.0	96.3**	46.2	45.9
	(0.5)	(0.6)	(0.5)	(0.4)	(0.9)	(0.8)
	Median value of assets or debt conditional on participation (EUR, thousands)					
Net wealth percentile						
<=20	5.3	3.4	0.8	0.4***	35.5	20.2
	(0.8)	(0.9)	(0.1)	(0.1)	(16.9)	(12.4)
20-40	49.4	39.6*	2.9	3.1	66.2	62.3
	(4.1)	(4.1)	(0.5)	(0.5)	(6.5)	(4.9)
40-60	89.9	75.3***	5.5	6	46.0	42.4
	(3.9)	(2.8)	(0.8)	(0.8)	(4.8)	(3.3)
60-80	161.9	133.7***	10.5	12	53.5	40.7**
	(6.3)	(5)	(1.1)	(1.8)	(5.1)	(3.3)
80-90	254.7	248.9	26.0	26.1	65.8	43.5
	(10.9)	(11.3)	(4.4)	(2.9)	(14.7)	(7)
>90	531.1	610.1	47.5	40.7	83.5	62*
	(35.6)	(32.9)	(7.3)	(6.7)	(10.1)	(6.1)
Total	112.0	101.9***	5.4	5.1	58.6	48.5***
	(2.5)	(1.8)	(0.4)	(0.4)	(2.7)	(1.7)

TABLE 9. Real wealth, financial wealth and debt, participation and median values: HFCS 2010 vs HFCS 2013

Notes: The HFCS 2010 values are adjusted by the consumer prices changes between the two waves of the survey. The values in parenthesis are the standard errors. ***, ** and * indicate that the test on the equality of the HFCS 2010 and HFCS 2013 statistics is rejected at 1 per cent, 5 per cent and 10 per cent, respectively.

In the remainder of this section, data on the different types of assets and liabilities is compared to understand the changes underlying these aggregate figures.

For most assets types, participation rates did not changed much in the period 2010-13 (Table 10). The main changes are an increase in the percentage of households with businesses and in the percentage of households with deposits. These trends hold across most household types.

	Real assets	Main residence	Other real estate properties	Self-employment business	Vehicles	Valuables
			Participation in assets (in %)			
HFCS 2010	91.5	76.0	29.1	9.3	73.5	8.0
	(0.5)	(1.1)	(1.1)	(0.7)	(0.8)	(0.8)
HFCS 2013	90*	74.7	30.3	12.7***	73.3	9.6
	(0.6)	(0.8)	(0.9)	(0.6)	(0.8)	(0.7)
			Median value of assets conditional on participation (thousand, EUR)			
HFCS 2010	112.0	107.9	70.5	54.0	6.0	2.7
	(2.5)	(0.9)	(5.7)	(5.9)	(0.5)	(0.8)
HFCS 2013	101.9***	91.3***	62.2	49	5**	5**
	(1.8)	(2.8)	(5.4)	(8.7)	(0)	(0.6)

	Financial assets	Sight accounts	Saving accounts	Tradable assets	Voluntary pensions schemes	Other
			Participation in assets (in %)			
HFCS 2010	95.0	93.7	44.8	7.5	16.1	9.2
	(0.5)	(0.6)	(1.1)	(0.6)	(0.9)	(0.6)
HFCS 2013	96.3**	95.6***	48.3**	8.1	17.2	10.5
	(0.4)	(0.4)	(1)	(0.5)	(0.7)	(0.6)
			Median value of assets conditional on participation (thousand, EUR)			
HFCS 2010	5.4	1.1	10.8	7.8	5.4	5.4
	(0.4)	(0.1)	(1)	(2.2)	(0.8)	(0.8)
HFCS 2013	5.1	1	11.1	4.9	4.9	5
	(0.4)	(0)	(0.9)	(0.7)	(0.5)	(0.5)

TABLE 10. Real wealth and financial wealth, participation and median values, by asset type: HFCS 2010 vs HFCS 2013.

Notes: The HFCS 2010 values are adjusted by the consumer prices changes between the two waves of the survey. The values in parenthesis are the standard errors. ***, ** and * indicate that the test on the equality of the HFCS 2010 and HFCS 2013 statistics is rejected at 1 per cent, 5 per cent and 10 per cent, respectively.

For the main asset types, with the exception of saving deposits, the median values are lower in 2013 than in 2010. However, when taking into account the uncertainty associated with this data, only in the cases of the main residence and vehicles are the changes statistically significant. The decrease in the median values of the main residence and vehicles are common to most types of households. These developments reflect, in the case of the main residence, the decline in house prices and, in the case of vehicles, probably their depreciation in a context where vehicle purchases recorded sharp falls. For other real estate properties and businesses, the median values changes are more heterogeneous across household groups. Its increase for the wealthiest households contributed to the more favourable evolution in the real wealth of these households.

As stated previously, the total percentage of indebted households remained broadly stable. There is however a differentiated evolution by debt type, with participation in mortgages on other real estate properties declining

	Total	HMR mortgage	Other property mortgages	Non-mortgage loans	Credit lines, overdrafts and credit cards
			Participation in debt (in %)		
HFCS 2010	46.2	34.0	5.7	13.4	8.9
	(0.9)	(0.9)	(0.5)	(0.9)	(0.7)
HFCS 2013	45.9	32.7	3.7***	17.3***	8.8
	(0.8)	(0.7)	(0.3)	(0.7)	(0.5)
	Median value of the outstanding debt conditional on participation (thousand, EUR)				
HFCS 2010	58.6	67.6	71.6	5.4	1.1
	(2.7)	(2.7)	(5.2)	(0.5)	(0.1)
HFCS 2013	48.5***	63.7	58.8*	4**	0.7***
	(1.7)	(2.2)	(5.7)	(0.4)	(0.1)

TABLE 11. Debt participation and median values by debt type: HFCS 2010 vs HFCS 2013.

Notes: The HFCS 2010 values are adjusted by the consumer prices changes between the two waves of the survey. The values in parenthesis are the standard errors. ***, ** and * indicate that the test on the equality of the HFCS 2010 and HFCS 2013 statistics is rejected at 1 per cent, 5 per cent and 10 per cent, respectively.

and participation in non-mortgage loans increasing (Table 11). Both trends are common to the majority of the different household types. However, by net wealth the reduction in the percentage of households with mortgages on other real estate properties was determined by the three highest classes. Participation of these wealthy households in main residence mortgages also declined, which is not observed for the lowest net wealth groups. These trends have contributed to the heterogeneous evolution of debt participation by net wealth classes referred above.

Among indebted households, the median amount of debt declined as compared to 2010. This reduction is common to all types of debt and is statistically significant in case of mortgages on other real estate properties, non-mortgage loans as well for debts associated with credit cards, credit lines and bank overdrafts. These debt types recorded reductions in median values for most households.

The HFCS includes the date on which loans have been granted. This information is useful to supplement the previous analysis on the participation rates. In the three years prior to the HFCS 2013, the number of households taking off new mortgage loans was higher in the highest wealth classes than in the lowest classes (Figure 6). Additionally, the share of households with high net wealth levels on the total number of households with new mortgage loans increased noticeably when compared to the HFCS 2010. For non-mortgage loans, the HFCS 2010 does not include information about the year of the contracts. However, among the households with non-mortgage loans in the three years prior to HFCS 2013, the share of households in the lowest wealth classes is slightly smaller than among all households that hold this type of

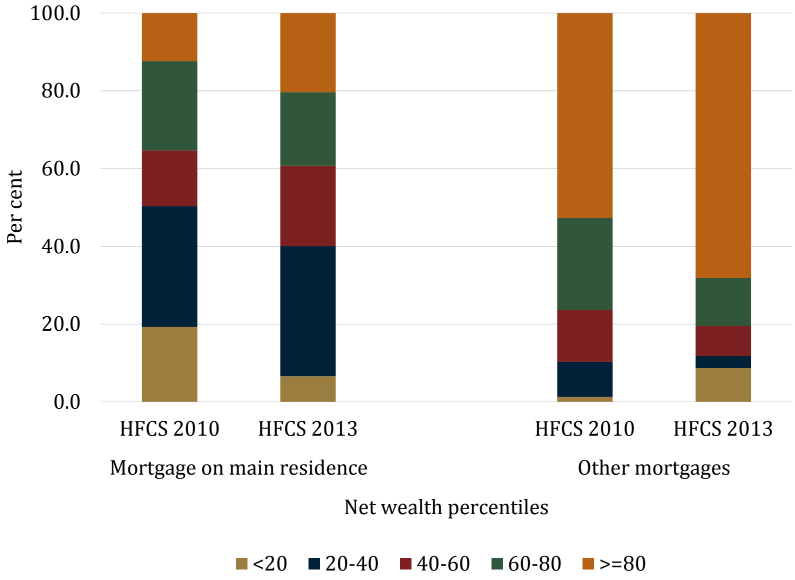

FIGURE 6: Composition of households with new mortgage loans: HFCS 2010 vs HFCS 2013.

Note: The new mortgage loans correspond to loans granted in the period 2007-10 in the case of the HFCS 2010 and in the period 2010-13 in the case of the HFCS 2013.

loans in 2013 (Figure 7). Thus, in general, the data suggests that, in the period between the two waves, the percentage of households with a more fragile financial situation taking off new loans has not been greater than in the past.

There is therefore no evidence that new loans have contributed to the evolution referred to above for the participation rates in debt. The reduction of participation in debt in the higher net wealth classes and their relative stability in lower net wealth classes, might have reflected alternatively the fact that among the households with a better financial situation, total loan reimbursements were more frequent or a change in household composition by net wealth classes. In fact, the decline in the real estate values leads to a more negative evolution of net wealth for leveraged households as compared to the remaining ones. This effect might have contributed to a change in the composition of the highest net wealth classes in favour of households with lower participation in debt.

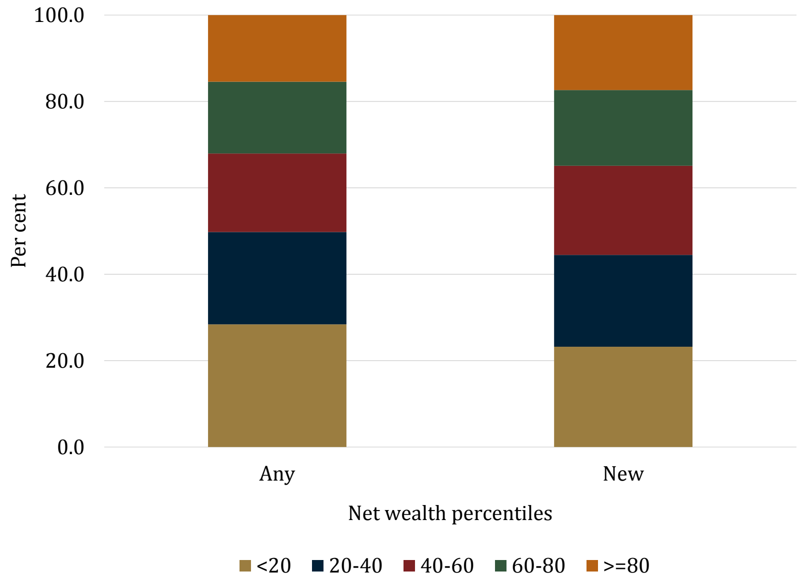

FIGURE 7: Composition of households with non-mortgage loans: Any loan vs new loans: HFCS 2013.

Note: The new mortgage loans correspond to loans granted in the period 2010-13.

Debt burden and vulnerabilities

In this section the HFCS data is used to analyse the degree of households' indebtedness and the burden of the debt service on income. With household level data it is possible to restrict the analysis to the indebted households and to identify the groups in which debt contributes more to a vulnerable financial situation. This analysis is important not only from the point of view of financial stability but also for the general macroeconomic analysis. Households with very high indebtedness levels and for whom debt service has a large weight on their income have a higher probability of defaulting and release fewer resources to be invested. Additionally, they are more likely to face liquidity constraints, which might lead to an excessive sensitivity of consumption to current income, hampering the efficient allocation of resources over time.

To evaluate the burden of debt on households' financial situation three indicators will be used: the debt service to income ratio, the debt to income ratio and the debt to assets ratio. The debt service ratio measures the ability of households to fulfil the short-term debt obligations, i.e., paying the loan instalments over a given period using only the income earned in that period.

	Debt-service income ratio	Debt-income ratio	Debt-asset ratio
	Median levels, for the indebted households (per cent)		
HFCS 2010	20.3	224.4	34.0
	(0.5)	(8.7)	(1.5)
HFCS 2013	16.8***	198.5**	37.8
	(0.5)	(8.2)	(1.8)
	Percentage of indebted households with ratios higher than:		
	40%	300%	75%
HFCS 2010	17.3	39.6	17.9
	(1.4)	(1.7)	(1.5)
HFCS 2013	12.3***	36.4	22.2**
	(1)	(1.3)	(1.3)

TABLE 12. Debt burden: HFCS 2010 vs HFCS 2013.

Note: The values in parenthesis are the standard errors. ***, ** and * indicate that the test on the equality of the HFCS 2010 and HFCS 2013 statistics is rejected at 1 per cent, 5 per cent and 10 per cent, respectively.

The debt to income ratio measures the household ability to pay off the debt based on annual income. This indicator is analogous to the debt ratios to GDP or to disposable income usually calculated with macroeconomic data. Finally, the debt to assets ratio is an indicator of household's solvency, meaning the percentage of assets the household would have to liquidate in order to be able to repay the entire debt. As in Costa and Farinha (2012a), to identify most vulnerable households, three threshold levels will be used: 40 per cent for the debt service to income ratio, 300 per cent for the debt to income ratio and 75 per cent for the debt to assets ratio.

In 2013, for the group of indebted households, the median debt service to income ratio stood at 16.8 per cent and the share of households with this ratio exceeding 40 per cent was around 12 per cent (Table 12). The heterogeneity by type of household is however very high. While in the lowest income class about half of the households are above the 40 per cent threshold, in the highest income class only about 2 per cent of households are in this situation. Compared to 2010, both the debt service ratio and the percentage of households with this ratio very high declined, in spite of the income reduction. This development has largely been determined by the reduction in Euribor rates, which are linked to about 90 per cent of mortgage loans in Portugal. The improvement in the debt service to income ratio was common to all classes of households, with the exception of those with unemployed reference persons. In these households the median ratio remained at about 20 per cent and the percentage of households with a ratio above 40 per cent increased from 23 per cent to 30 per cent.

The median debt to income ratio was around 200 per cent in 2013, showing a slight decrease compared to 2010. Despite this positive development, more than a third of the indebted households still have ratios above 300 per cent. The incidence of households with very high levels of debt as compared to income is particularly high for the lowest income and wealth classes, and, reflecting the age profile of the main residence mortgages, for households with younger reference persons. In the two lowest age groups, about 50 per cent of the households have a ratio greater than 300 per cent.

In 2013, the median debt to assets ratio stood at around 38 per cent and was higher than 75 per cent for one fifth of the indebted households. In the lower income class and in households with younger or unemployed reference persons this situation is common to almost 40 per cent of the households. The percentage of households with this ratio high showed an increase as compared to 2010. The unfavourable development in the assets values and, in particular, in real assets contributed to this trend.

The percentage of indebted households with the three ratios above the critical values remained between 2010 and 2013 at around 4 per cent. The highest incidence of households in this situation occurs in the lowest income class (16.2 per cent), in the lowest age group (9.6 per cent), when the reference person is unemployed (10.4 per cent), in households with one adult and children (12 per cent) and in households in the lowest net wealth class (17.1 per cent).

In the HFCS households are asked if they have had late or missed payments on loan instalments in the twelve months prior to the survey. In line with the conclusions reached for HFCS 2010 in Costa (2012), in households reporting default on debt payments, the existence of very high debt ratios (especially, debt service to income ratio higher than 40 per cent) or some negative shock to their financial situation is more frequent than in households not reporting default (Figure 8).

Credit demand and credit constraints

In the three years prior to 2013, about 14 per cent of Portuguese households have applied for credit and, of those who made these requests, about 13 per cent saw their applications refused (Table 13). In addition, about 6 per cent of the households gave up applying for credit because they anticipated the request would be refused. If we define a household to be credit constrained when at least one of the above situations occur, about 7 per cent of the Portuguese households were credit constrained in 2013.

The incidence of credit constraints reaches maximum values (of about 13 per cent) for households with lower levels of net wealth, as well as when the reference person is younger or unemployed. Among the indebted households, credit constraints are more frequent for households with very high debt ratios or debt service to income ratios. Compared to 2010, although there was a slight increase in the percentage of households that anticipated refusals of

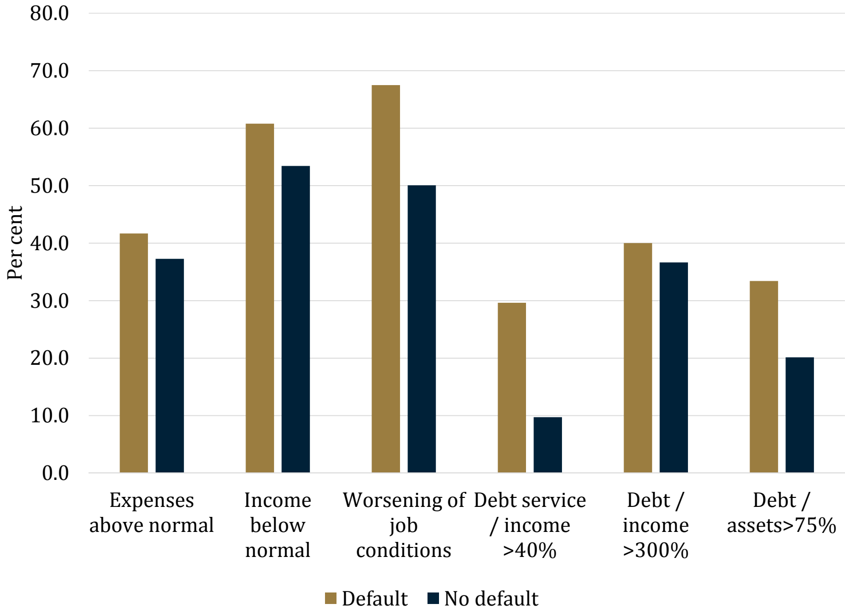

FIGURE 8: Negative shocks and debt burden among households with and without defaults: HFCS 2013.

Notes: The bars for households with default (no default) represent the percentage of households, who had been subject to a negative shock or with high debt burdens, on the total number of households with (without) late or missed payments on loans in the 12 months prior to the interview. The negative shocks are the following: income in the previous year below normal; last 12 months regular expenses above normal; deterioration of the situation at work (for example, job loss or reduction in income) in the three years prior to the survey, for any household member working at some point in time during this period.

	Applications for credit	Refusals	Perceived credit constraints	Credit constraints
	(% of total households)	(% of households that applied)	(% of total households)	(% of total households)
HFCS 2010	23.4	14.2	4.1	6.0
	(0.9)	(1.6)	(0.5)	(0.6)
HFCS 2013	14.4***	13.3	5.7**	7.1
	(0.7)	(1.7)	(0.5)	(0.5)

TABLE 13. Applications for credit and credit constraints: HFCS 2010 vs HFCS 2013.

Note: The values in parenthesis are the standard errors. ***, ** and * indicate that the test on the equality of the HFCS 2010 and HFCS 2013 statistics is rejected at 1 per cent, 5 per cent and 10 per cent, respectively.

their loan applications, credit constraints have not increased significantly. The main change in this period has been a reduction in the percentage of

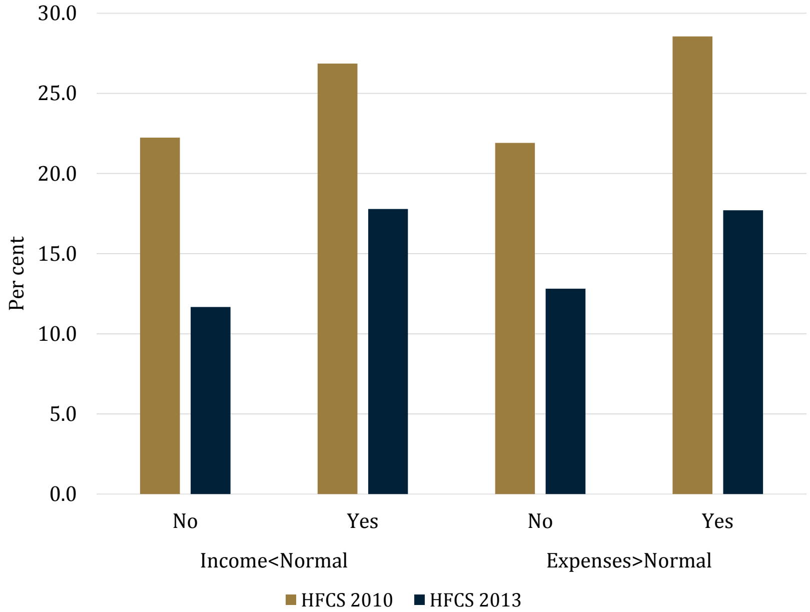

FIGURE 9: Households that applied for credit and shocks on income or expenses: HFCS 2010 vs HFCS 2013.

Note: The Yes (No) bars represent the percentage of households that applied for credit in the last three years among the total number of households that had (did not have) income below normal in the previous year or regular expenses higher than normal in the last 12 months.

households applying for credit. This decrease compared to 2010 was also observed when one considers not only the households who have applied, but also those that gave up applying due to perceived credit constraints. This data suggests demand for credit had an important role in explaining the reduction in the amount of credit granted. The decrease in demand was widespread in almost all household types, but was more pronounced in households with higher levels of income and wealth, as well as in households whose reference person is younger, has a higher level of education or is working. Among the households with income below normal or expenses above normal, the incidence of loan applications is higher than for the remaining households. This suggests that, despite the high uncertainty prevailing and the increase in precautionary savings, households have continued during this period to seek to smooth consumption using credit (Figure 9).

Conclusions

The results of the second wave of HFCS confirm the patterns of the distributions of wealth, income and consumption by household types identified with the first wave data. Net wealth is higher for households that also have higher levels of income and when the reference person is in the age class before retirement, has a higher education level or is a self-employed. Real estate has a dominant weight in the wealth of most households. About 75 per cent of Portuguese households own their main residence and about 30 per cent are owners of other real estate properties. Deposits are the most important financial asset for all household types, representing more than 65 per cent of total financial wealth. Participation in more risky financial assets is far more heterogeneous, increasing much more sharply with income and net wealth, than participation in deposits. Financial wealth is more unevenly distributed than real wealth. Debt also has a very skewed distribution, reflecting the fact that around 55 per cent of households in Portugal have no debt. The most frequent type of debt are mortgages on the main residence and the second type loans not using real estate properties as collateral (respectively, about 30 and 17 per cent of households have these types of debt). The share of non-mortgage loans on total debt is higher for households with lower income levels, than for in the one with higher incomes.

In the second quarter of 2013, the mean net wealth of households was around 160 thousand euros, while the median stood at less than half of this amount. Compared to 2010, the median net wealth declined slightly in real terms. The change in the mean net wealth was not significant. In fact the decrease in non-financial wealth seems to has been offset by a reduction in the mean levels of debt, while financial wealth remained broadly constant. The decline in real wealth was to a large extent determined by a decrease in the value of the main residence, which was broadly based across the different household types. The reduction in the amount of debt held by households seems to have been largely the result of the normal process of loans amortizations, in a context where the new loans granted declined. The HFCS data suggests the reduction in demand for credit by households has had an important role in explaining the decline in the loans granted during the period 2010-13.

The percentage of total net wealth held by the households in the bottom of the net wealth distribution in 2013 was slightly smaller, than the percentage of net wealth held by the same type of households in 2010. This change was to a large extent driven by a decline in the real wealth of the households in the lowest net wealth classes in 2013 as compared to the ones that were in the same classes in 2010. In addition, households in the upper net wealth classes in 2013 held less debt than households that were in these groups in 2010. The HFCS data suggests that in the period between 2010 and 2013, the percentage of households with new loans was less concentrated than in the past in households with a more fragile financial situation. In these conditions, the decline in the debt concentration on the wealthiest households might have resulted from a change in the composition of households that are in the top wealth classes in favour of households with lower debt levels or from the fact that households with a better financial situation have made higher total loan repayments than the remaining ones.

In the period 2010-13, the debt service to income ratio declined for most household types. Given the decline in income, the favourable evolution of the debt-service ratio is to a large extent explained by the decline in the Euribor interest rates. The levels of debt compared to income remained however very high for more than a third of the indebted households. In addition, the percentage of households with very high debt levels relative to the value of assets increased, reflecting the reduction in the value of real wealth. Households with lower levels of income or net wealth, composed by an adult and children, as well as those whose reference person is younger or unemployed are the ones for which debt has a higher burden on the financial situation.

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Appendix A: Methodological issues

This appendix presents the main methodological aspects of HFCS and some indicators on the sample and the response rate. A special focus is given to the changes introduced in second wave which impacted the questionnaire, the sample design and the weighting. The methodological features of HFCS are described in more detail in Costa and Farinha (2012b). In addition, a comparison of the methodology of Portuguese HFCS with the other surveys participating in this project can be found in HFCN (2013a) e HFCN (2016a) for the first and second waves, respectively.

A.1. Questionnaire

Table A.1 includes the reference units and reference periods for the nine main sections of the questionnaire. The fieldwork period for the first and the second wave took place during the second quarters of 2010 and 2013, which means these are the reference periods for assets and liabilities.[11] The references periods for income are 2009 in the HFCS 2010 and 2012 in the HFCS 2013.

In order to maintain comparability of data, only minor changes were introduced in the second wave questionnaire. The main changes consisted in the introduction of some new questions. In case of loans renegotiations, households are now asked about the reasons for such renegotiations and on whether these were associated with difficulties in paying the loan instalments. In addition, non-mortgage loans were broken down into loans from relatives or friends and other loans. For the latter, the date at which the loan was taken is now collected, similarly to what already occurred with mortgage loans. In case of late or missed payments on loan instalments, households are now asked about the type of loan in which these situations have occurred. In the case of businesses, the year the household began to participate and the volume of sales in the previous year (i.e. in 2012) are now collected. Regarding financial assets, households began to be asked about the ownership of deposits in a currency other than the euro and on the existence of some financial assets deposited abroad. In addition, money owed to the household was broken down into loans made to businesses owned by the household and into other receivables. In the labour market section, individuals who are not working at the time of the interview but have worked previously, are now questioned about the year they stopped being employed and about the job they had for most of their active life. Finally, for vehicles some questions were introduced about its purchase in the past 12 months.

11. Strictly speaking a small percentage of interviews in the HFCS 2013 were made in early July 2013.

Section	Reference unit	Reference period
1. Demographics	Individual	Time of the interview
2. Real assets and mortgages	Household	Time of the interview
3. Other liabilities	Household	Time of the interview
4. Businesses and financial assets	Household	Time of the interview
5. Labour market situation	Individual (age >=16)	Time of the interview
6. Rights over future pensions	Individual (age >=16)	Time of the interview
7. Income	Individual (age >=16) and Household	Last calendar year
8. Inheritances and gifts	Household	-
9. Consumption and saving	Household	Typical month

TABLE A.1. HFCS Questionnaire.

A.2. Sample design

The sample design of HFCS aims to obtain representative data of households living in Portugal and of the wealth held by these households. Since much of the wealth, and in particular the financial wealth, is concentrated in a relatively small number of households, a part of the HFCS sample is designed with the objective of picking up wealthy households. The HFCS gross sample is composed by 8000 private dwellings used as main residences: 4000 selected in order to be representative of the population in Portugal (with the geographical criteria usually used in the household surveys conducted by Statistics Portugal), and 4000 selected in order to oversample the wealthy. As compared to the first wave, some changes were introduced in the sample design due to a change in the sampling frame used by Statistics Portugal in the household surveys. In the first wave, the sampling frame consisted of a sample extracted from the 2001 Census (Master Sample) and the sub sample of the wealthy consisted in dwellings from the metropolitan areas of Lisbon and Oporto, regions where the available evidence pointed to a higher probability of finding wealthy households. For the HFCS 2013, the sampling frame changed to the National Dwellings Register, in line with what happened with other household surveys conducted by Statistics Portugal. As compared to the Master Sample, this new sampling frame has the advantage of including all the private dwellings used as main residences in Portugal and of including more updated information, since it was built from the Census 2011 data. In addition, the National Dwellings Register includes information about the size of the dwellings, which, according to the data of HFCS 2010, is more correlated with household wealth than the geographical location. Taking this into account, in the HFCS 2013, the sub sample of the wealthy consisted in dwellings bigger than certain limits in square meters set by region based on HFCS 2010 data.

A.3. Data processing

After collection, the data were extensively analysed. Whenever possible the errors and inconsistencies detected were corrected. Additionally, the answers considered implausible were dropped. Since non-response to survey questions (item non-response) are in many cases related to the characteristics of the households, the existence of missing data may bias the conclusions draw with the data. Thus, after the data editing, the missing answers for the main variables (which are mainly due to answers of “Don´t know” or "No answer" by the households) were imputed through a multiple stochastic imputation model. The imputation originates five imputed values (replicates) for every missing value, taking into account the uncertainty associated with the imputation process. Finally, the data were anonymised in order to ensure that households or individuals participating in the survey cannot be identified based on the answers given.

A.4. Weighting

Because the HFCS sample is not a simple random sample (i.e., the probability of selection differs among elements of the population), to calculate population statistics it is necessary to use weights that represent the number of households in the population that are similar to each household in the sample. As described in Costa and Farinha (2012b), the HFCS weights besides reflecting the likelihood of each household being selected for the gross sample, are corrected for the unit non-response (i.e., by the fact that not all selected households have participated in the survey), and calibrated to align the distributions of some variables in the sample with their distributions in the population. In HFCS 2013, the variables used in the calibration model were the sex and age group, the size of the households, the number of households by region and the outstanding amount of mortgage loans by region. This calibration method differs from the one used in the first wave because it now includes the outstanding amount of households mortgage debt and more age classes.

In order to minimize the impact of the above methodological changes in the comparability of data between the two waves, the HFCS 2010 weights and their replicates were recalculated. In this revision the more updated estimations for the population in 2010, which became available after the release of Census 2011, were used. Additionally, the calibration model was changed to be in line with the one used in the second wave. The HFCS 2010 data presented in this article incorporate this revision of weights, differing so slightly from the data previously disclosed.

	HFCS 2010	HFCS 2013	Change (% or p.p.)
Response behaviour			
(In number of sample units)			
Gross sample	8000	8000	0
Net sample	4404	6207	41
Non-response			
Non-contacted	1343	565	-44
Refusals	711	371	-71
Other reasons for non-response	375	154	-66
Not eligible	1122	675	-41
Unknown eligibility	45	28	-38
(In percentage)			
Response rate (net sample/eligible)	64	85	21
Refusal rate (refusals/eligible)	10	5	-5
Cooperation rate (net sample/contacted)	80	92	12
Contact rate (contacted/eligible)	80	92	12
Elibility rate (eligible/gross sample)	86	92	6
Oversampling			
% of HH in the net sample with net-wealth higher than:			
p90 of net-wealth in the population	10.9	15.6	-
p95 of net-wealth in the population	5.7	7.4	-
p99 of net-wealth in the population	1.2	2.0	-

TABLE A.2. Sample outcome statistics.

Notes: In the eligible households are included a share of the sample units for which eligibility is unknown. The contacted sample units include the households in the net sample as well as the sample units that were contacted but have not participated in the survey because of refusals and other reasons for non-response. The other reasons for non-response include for instance cases of non-response due to illness or incapacities.

A.5. Indicators on the sample and response rate

The final database of the second wave includes 6207 households, compared with 4404 households in the first wave (Table A.2). The update of the sampling frame has contributed to this very significant increase in the net sample. In fact, there was a significant decline in the number dwellings that were not eligible (namely, because of not being main residences).

In addition to the increases in the eligibility rate, there was also a very sharp increase in response rate. This was mainly the result of a reduction in the number of households non-contacted (because of being absent) and in the number of households who refused to participate in the survey. The response rate increased from 64 per cent in the first wave, to 85 per cent in the second wave, standing in both waves at very high levels, as compared with those of other countries participating in this project.

Another aspect that is important to evaluate is the degree of oversampling of the wealthy households. In the second wave, the percentage of households in the net sample with net wealth higher than the percentiles 90th and 99th of the net wealth in the population, stood respectively at 15.6 per cent and 2.0 percent (10.9 per cent and 1.2 per cent in the first wave). The improvement in these indicators suggests a greater efficiency of the new oversampling methodology. These values remain, however, well below those obtained in surveys of countries where administrative data on income or wealth of individuals is used to oversample the wealthy households (HFCN (2016a)).

Appendix B: Definitions of variables

B.1. Assets, debts, income and consumption

Net wealth is the difference between the gross wealth (value of all real and financial assets) and the value of total debt at the time of interview.

Real wealth (or non-financial wealth) includes the main residence, the other real estate properties, the motor vehicles, the self-employment businesses and other valuable assets that the household owns.[12] The category of other valuable assets consist of, for example, jewellery, antiques and works of art. Self-employment businesses correspond to the value of the participation of the household in non-publicly traded businesses, in which any household member works as self-employed or has an active role in running the business.

Financial wealth includes sight deposits, saving deposits, financial tradable assets, voluntary pension plans and other financial assets. Similar to what happens in the Financial accounts, Savings Certificates and Treasury Certificates are included in saving deposits. Tradable assets include mutual funds, debt securities and quoted shares. The value of the voluntary pension plans correspond to the accumulated investment (by the household members' initiative) in financial products that provide income later in life (e.g., pension funds that are not associated with the professional activity, retirement savings plans or insurances ensuring a pension). Other financial assets include: the value of participations in unquoted businesses, in which any household member participates only as an investor; money owed to the household as

12. This definition of real assets differs from the definition in the National Accounts, namely because it includes vehicles and businesses.

private loans (for example, loans to friends, relatives or to self-employment businesses); managed investment accounts; and any other financial asset that was not yet accounted for in the preceding items (e.g., financial derivatives or patents).

Debt corresponds to the outstanding amount of loans having real estate properties as collateral (mortgages on the main residence or on other real estate properties), the outstanding amount of other loans and the outstanding amounts of bank overdrafts, credit lines or credit cards debts.

Household income is the sum of all gross income of the household members (i.e., it corresponds to the income before the payments of taxes and mandatory retirement contributions by the workers). The income sources are: employee income; self-employment income; public pensions (old age, retirement, survivors or disability pensions); private pensions (from occupational plans or voluntary pension plans); unemployment benefits; other regular transfers from the public sector (for example, family allowances, scholarships or other welfare payments); regular private transfers (e.g. alimony, scholarships or other grants); income from real estate properties; income from financial investments (for example, interest and dividends); income from unquoted businesses (excluding self-employment income); and also from other sources (e.g. capital gains or losses from the sale of assets or severance payments). In Figure 3 pensions includes public and private pensions and other transfers include unemployment benefits, other regular benefits from the public sector and regular private transfers.

Consumption corresponds to regular household expenditure on non-durable goods and services. In the HFCS, this amount is collected in aggregate terms, as well as disaggregated in the following items: food at home; food outside home; utilities and other regular expenses in non-durable goods and services. The data is collected in monthly values for the typical month. For this article, the figures collected were multiplied by twelve in order to reflect annual values.

B.2. Demographic and socioeconomic characteristics of households

The households' characteristics considered are the age, work status and education level of the reference person, the net wealth and income of the household, and the household size. Aside from income, which refers to 2012, the other variables refer to the time of the interview (i.e., the period from March to July of 2013).

The reference person is selected according to Canberra definition. In this definition the following sequential criteria are applied until a single household member is chosen: 1) a member of a couple with dependent children; 2) a member of a couple without dependent children; 3) a lone parent with dependent children; 4) the person with the highest income; and 5) the eldest person.

The age classes correspond to: less than 35 years old; between 35 and 44; between 45 and 54; between 55 and 64; between 65 and 74; and 75 years old or more.

The work status distinguishes employees, self-employed, unemployed, retired and other situations of inactivity, which include, for example, students, permanently disabled and individuals doing unpaid domestic tasks.

The education levels considered are: below secondary, secondary and tertiary. In terms of the scale of International Standard Classification of Education from 1997 (ISCED-97), these levels correspond, respectively, to: below or equal to ISCED2; ISCED3 and ISCED4; and ISCED5 and ISCED6.

Income and net wealth classes are defined according to the percentiles of these variables in the population, i.e., in the weighted sample. The following classes are considered: less or equal to the 20th percentile; between the 20th and the 40th percentiles; between the 40th and the 60th percentiles; between the 60th and the 80th percentiles; between the 80th and the 90th percentiles; and higher than the 90th percentile A percentiles is a unit that divide the sample ordered by ascending order of data in 100 equal parts. Thus, for example, a net wealth of 71 thousand euros for the 50th percentile, means that 50 per cent of households have net wealth lower than that amount.

Bank Switching in Portugal

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Abstract
Using the population of firm-bank exposures from 2007 to 2014, bank switching in Portugal is studied. A firm is said to switch from the inside bank to the outside bank when it establishes a soft information relationship with the outside bank. It is found that the probability with which firms switch banks is related to macroeconomic, firm, bank, and firm-bank relationship factors previously studied in the banking literature. The probability of switching is procyclical, and firms are more likely to switch from worse capitalized banks. Firms are more likely to switch if they have greater turnover, lower return on assets, are less opaque or are growing faster. Firms are also more likely to switch when they have longer bank relationships or a greater number of bank relationships. Riskier firms are more likely to switch and maintain their exposure to the financial system, while safer firms are more likely to switch and increase their exposure to the financial system (JEL: G21, L11, L14)

Introduction

Bank relationships bring advantages and disadvantages to firms. Boot and Thakor (1994) show that bank-borrower relationships are welfare-enhancing by increasing contract flexibility, and Rajan (1992) defend that bank relationships reduce agency problems in lending. The empirical literature shows that the development of bank relationships improves loan conditions for firms. In specific, it has been shown that firms with longer bank relationships enjoy lower collateral requirements (Menkhoff *et al.* (2006), Lehmann *et al.* (2004), Peltoniemi (2004), Ziane (2003), and Degryse and Van Cayseele (2000)), longer loan maturities (Bodenhorn (2007)) and better access to credit (De Bodt *et al.* (2005) and Lehmann and Neuberger (2001)). On the other hand, firms have incentives to avoid relationship banking. Banks have bargaining power over firms' profits (Rajan (1992)), and firms have to bear hold-up costs (Sharpe (1990)).

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Given the documented benefits and disadvantages of bank relationships, it is important to understand why firms decide to resort to a new bank instead of using their existing relationship. In this article I study how the probability that firms switch banks and form new bank relationships is related to macroeconomic, bank, firm and firm-bank relationship factors previously studied in the literature.

I establish a definition of switch that is consistent with the literature on this topic, namely Ioannidou and Ongena (2010) and Bonfim *et al.* (2016), and that captures the creation of information links between the firm and a new bank - which I will call the *outside bank*. I say that firms switch banks when they establish a relationship with the outside bank and have a relationship with at least one other bank - the *inside bank* - for at least 12 months.

The relationship with the inside bank has to last for at least 12 months so that this bank has enough time to capture private information about the firm. Firms may still maintain their relationship with the inside bank after establishing a relationship with the outside bank.

I characterize switching activity in Portugal from 1981 to 2014 and show that the number of switches grew until 2008 and then dropped from 2009 onwards, while the percentage of switching firms remained stable between 1987 and 2010 and dropped in 2011. I provide descriptive statistics of the firm, bank, and firm-bank relationship variables that are related to the probability of switching.

The relationships between the probability of switching and other variables studied in the literature seem to hold in the Portuguese case. Firms value more bank relationships and are less likely to switch if they are more opaque. This evidence is consistent with the hypothesis by Rajan (1992) that the benefit of relationship banking arises from the information banks can extract from firms. Switching is also less prevalent among smaller firms, which is consistent with the idea that small firms depend on relationship banking because they are more affected by issues of asymmetric information than larger firms.

Farinha and Santos (2002) find empirically that poorly performing firms establish new relationships to substitute financing from one bank to another. My results are consistent with their findings, as firms with lower return on assets are more likely to switch to a new bank.

Additionally, I find that riskier firms are more likely to switch and keep a constant credit exposure, while safer firms are more likely to switch and increase their exposure to the financial system significantly. To arrive to this conclusion I divide firms in four quartiles according to the growth of their exposure to the financial system and measure the probability that they switch banks and simultaneously belong to one of the quartiles. Firms that switch and do not increase their exposure to the financial system significantly (i.e. belong to the second and third quartiles) seem to have a higher probability of default. For the fourth quartile, riskier firms are less likely to switch.

On the bank side, Berger *et al.* (2005) defend that small banks specialize in small firms for which soft information is more valuable. Gopalan *et al.* (2011) also find empirically that firms establish relationships with larger banks with greater capacity to finance new projects. Even though we find that firms switch from banks with lower Tier 1 ratios, the transition phenomenon from smaller to larger banks is not significant in the Portuguese case.

In macroeconomic terms, switching happens more often in economic expansions than in contractions. This evidence is consistent with the model from Hale (2012) - global downturns or downturns in small countries reduce financial links among banks in the long term and consequently loan originations by individual banks.

The article starts with a review of the previous literature on bank relationships in the *literature* section. The *data and variables* section describes the data sources used in the analysis and contains descriptive statistics for switching and nonswitching relationships. In the *regression analysis* section I explore the relationships between the factors identified in the literature and the probability of switching through regression analysis. In the *switcher heterogeneity* section I study how the determinants of bank switching differ between firms that increase significantly or maintain their credit exposure. The conclusion summarizes the main findings of the article.

Literature

Previous literature shows that firm and bank relationships have benefits and costs for firms. In the model of Rajan (1992) firms share part of the profits of their projects with the bank, and firm owners keep the residual value of the project. Informed banks add value because they only allow firms to continue projects that have positive net present value. However, there are disadvantages to bank relationships. Firm owners have to share part of the value they create with banks, which reduces their incentives to exert effort. Competition reduces the share of the net present value that banks extract from firms. On one hand, competition reduces the control of banks over firms. On the other hand, firm owners have greater incentives to exert effort, as they now have access to a greater share of projects' net present value.

Boot and Thakor (1994) model bank relationships and find that their value increases over time because firms have access to loans with more flexible conditions if they have a history of successful projects. Conversely, Sharpe (1990) and Von Thadden (2004) develop a theoretical framework where bank relationships are costly for firms because they generate hold-up costs. Banks with firm relationships have private information about these firms, and use it to extract rents. Ongena and Smith (2001) finds empirically that the probability of switching increases with relationship duration, which gives support to the idea that bank relationships lose value with time.

Petersen and Rajan (1994) show empirically that smaller firms value relationship banking more than large firms, and that as firms grow they tend to establish more relationships with more banks. According to Berger and Udell (1995), smaller firms value bank relationships because they are an important mechanism to solve problems associated with asymmetric information. Cole (1998) also finds that bank relationships are more valuable for firms with greater information asymmetries, and that the private information a bank generates about a firm is less valuable when the firm has multiple sources of financial services.

Gopalan *et al.* (2011) study how bank relationships are affected by bank characteristics. Smaller banks tend to specialize on smaller firms for which the acquistion of information is important to guarantee credit quality. These firms tend to switch from smaller to larger banks as they grow, as small banks have no capacity to lend to larger firms.

Farinha and Santos (2002) show empirically that firm performance is related to the probability that firms switch from single to multiple relationships. High-growth firms are more likely to borrow more in the future, and for them hold-up costs are more significant. Hence, these firms have greater incentives to establish multiple relationships than low-growth firms. Banks also have incentives to diversify risk and limit lending to worse performing firms. Because of such constraints, firms are more likely to find alternative lenders.

The macroeconomic cycle also has an impact on the formation of bank relationships. According to Hale (2012), when there is a global economic downturn or a local economic downturn banks establish fewer financial relationships among themselves in the long run. Banks that establish fewer relationships with other banks are also less likely to originate new loans.

Data and variables

Firm-bank relationships are retrieved from the Portuguese Credit Register (*Central de Responsabilidades de Crédito*). This database contains monthly information about loans from financial institutions registered in Portugal to non-financial institutions. Observations related to public administration bodies and non-profits were dropped to have a data set exclusively of non-financial corporations. Potential loans such as unused lines of credit are considered in the determination of the main lender. Company data is retrieved from IES (*Informação Empresarial Simplificada*). This data set spans from 2005 to 2013 and contains annual financial statement data for Portuguese non-financial corporations. Bank-level data is retrieved from Monetary Financial Statistics (*Estatísticas Monetárias e Financeiras*), a mandatory quarterly report from financial institutions registered in Portugal and from mandatory bank prudential reports.

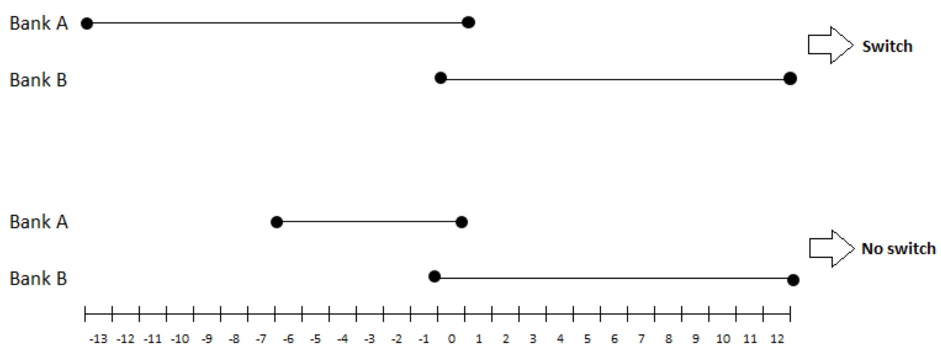

FIGURE 1: **Examples of switching and non-switching relationships with banks A and B.** Firm i switches from bank A to bank B at $t = 0$ in the first case because it establishes a relationship with bank B for at least 12 months and at $t = 0$ it had a relationship with bank A for at least 12 months. Firm i does not switch from bank A to bank B at $t = 0$ in the second case because it did not have a relationship with bank A for at least 12 months.

The definition of switch used in this article is similar to the one used by Ioannidou and Ongena (2010) and Bonfim *et al.* (2016) and is illustrated in figure 1. Two requirements must be observed for a new bank relationship to originate a bank switching event. First, the new relationship should be obtained from a bank with which the firm did not have a relationship during the previous twelve months. The relationship with the new bank must last for at least 12 months. This bank is called the outside bank. Second, the firm must have had at least one relationship lasting at least 12 months with at least one other bank. This bank is the inside bank. All new relationships that do not observe these two conditions do not generate bank switches.

Figure 2 shows the number of bank switches and the percentage of firms in the financial system that switch banks at least once from 1981 to 2014. The number of switches increased steadily from approximately 5,000 switches in 1981 to 30,000 switches in 2008. This increase in the number of switches seems to be propelled by an increase in the participation of firms in the financial system, as the percentage of firms that switched actually decreased in that period from about 15% in 1981 to 11% in 2008. After 2008 the number of switches and the percentage of switching firms decreased, which suggests that global economic downturns have negative effects on switching. There was a negative shock in both the number of switches and the percentage of switching firms in 2012.

Table 1 summarizes the descriptive statistics for switching and non-switching bank relationships. I measure the size of switching and non-switching firms using their turnover. I build an opaqueness index by

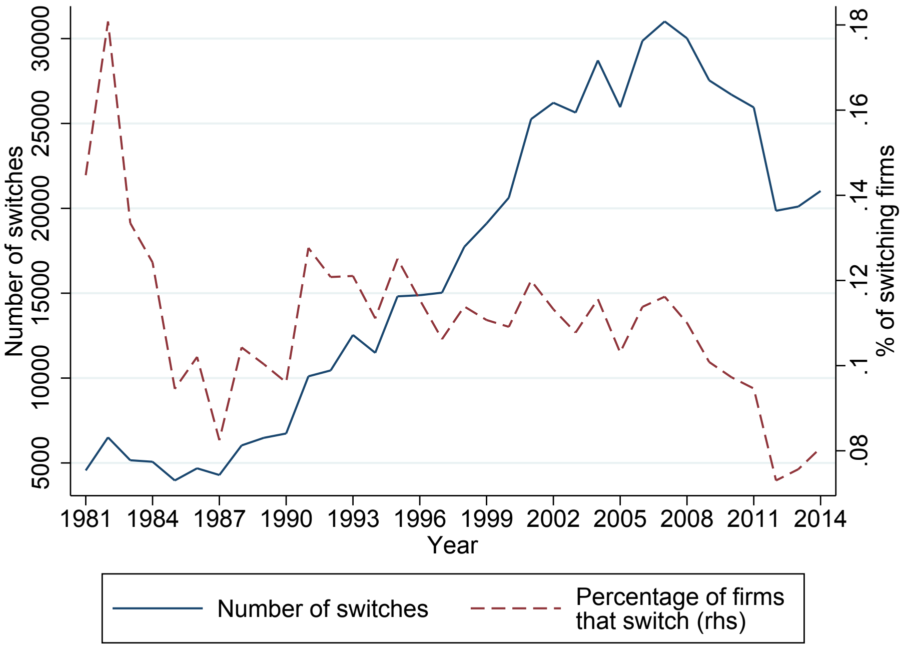

FIGURE 2: **Number of switches and percentage of switching firms.** The figure above represents the number of switches between 1981 and 2014. The straight line shows the number of switches per year and the dashed line (rhs) the percentage of firms that switched banks in each year.

calculating the percentage of fields in IES that are not reported for each firm. I assume that firms with a higher share of unavailable accounting information are more opaque. Turnover growth measures whether firms are growing or not. Antunes *et al.* (2016) calculate the probability of default for Portuguese firms. These probabilities of default are calculated every year. At the relationship level, I measure the duration and number of bank relationships. A detailed description of each of these variables can be found in table A1.

In order to eliminate the impact of extreme outliers, I trim revenue growth, return on assets and bank leverage at the 5% and 95% levels. I also trim firm age at the 99% level.

Table 1 shows the characteristics of switching and non-switching bank relationships in various dimensions. On average, switching firms are older, larger and more transparent. They also have on average higher growth and lower return on assets. These firms are also on average less levered and have a lower probability of default. The percentage of defaulted relationships for switching firms is lower than for non-switching firms as well. Switching firms

	Switching relationships			
	Obs.	Mean	St. Dev.	Median
Firm characteristics				
Age (years)	400,044	15.1***	11.5***	12***
Turnover (EUR Million)	404,844	6.0***	76.1***	0.7***
Opaqueness index (%)	404,844	9.9***	6.0***	8.7***
Turnover growth (%)	362,398	7.1***	30.3***	2.6***
ROA (%)	295,830	2.6***	3.0***	1.4***
Bank leverage (%)	353,402	25.3***	18.1***	21.9***
Prob. default (%)	254,288	4.6***	5.3***	2.9***
Relationship characteristics				
Defaulting relationship (%)	430,326	8.9***	28.3***	0.0***
Duration (years)	430,326	6.9***	6.0***	4.8***
Number of relationships	428,955	3.1***	1.9***	3.0***
Bank characteristics				
Bank assets (EUR Million)	429,575	51,981***	38,182***	47,400***
Tier 1 Ratio (%)	311,356	8.4***	9.4***	9.0***

	Nonswitching relationships			
	Obs.	Mean	St. Dev.	Median
Firm characteristics				
Age (years)	28,660,596	14.4	11.1	11
Turnover (EUR Million)	28,948,634	3.1	48.0	0.3
Opaqueness index (%)	28,948,634	11.9	7.5	10.3
Turnover growth (%)	24,628,796	2.9	30.4	-0.1
ROA (%)	17,611,111	2.9	3.3	1.6
Bank leverage (%)	22,541,151	25.9	19.4	21.7
Prob. default (%)	14,126,869	4.7	5.5	2.9
Relationship characteristics				
Defaulting relationship (%)	36,252,183	16.8	37.4	0.0
Duration (years)	36,252,183	6.3	5.8	4.6
Number of relationships	35,757,971	2.4	1.7	2
Inside bank characteristics				
Bank assets (EUR Million)	36,202,512	54,860	38,540	48,262
Tier 1 Ratio (%)	27,049,889	8.9	11.3	9.2

TABLE 1. **Selected Characteristics of Switching and Nonswitching Relationships.** I report the mean, standard deviation, and median for selected firm, relationship and bank characteristics. The unit of observation in this table is the number (n) of switching and nonswitching loans with monthly periodicity. I assess the differences in means using the Student's t-test. I assess the differences in medians using the Wilcoxon-Mann-Whitney test for continuous variables and the Pearson's Chi-square test for categorical variables. I assess the differences in standard deviations using Levene's test. I indicate whether the differences between the corresponding means, medians and standard errors are significant at the 10%, 5%, and 1% levels using *, **, and ***, respectively. See table A1 for the meaning of each variable.

are more likely to have longer relationships and a greater number of bank relationships. At the bank level, firms switch from slightly smaller banks with lower Tier 1 ratios.

Regression Analysis

Model description

In this section I test whether individual firm, bank, and bank relationship characteristics described in the *data* section are related to the probability that firms switch banks, conditional on the remaining characteristics. I observe if the firm switches to a new bank for each bank relationship every month between January 2007 and December 2014[1].

The basic regression model is given by equation 1:

$$Pr(Q_{i,b,t} = 1) = f(Firm_{i,t}, Bank_{b,t}, Relationship_{i,b,t}, Macro_t) \tag{1}$$

$Pr(Q_{i,b,t} = 1))$ is the probability that firm i switches from bank b at month t. This probability is modelled as a logistic function of firm characteristics $Firm_{i,t}$, bank characteristics $Bank_{b,t}$, firm-bank relationship characteristics $Relationship_{i,b,t}$, a macro variable measuring GDP growth $Macro_t$. I include bank and time fixed-effects as control variables.

Main results analysis

Table 2 reports coefficients for regression 1. I include standard errors clustered at the bank level in parentheses and marginal effects in brackets. Date, bank and firm activity sector controls are included in the regression but these results are not reported.

In column 1 I use a smaller set of variables to increase the number of observations included in the regression. In column 2 I repeat the exercise but include variables for ROA and bank leverage. In column 3 I do not use time fixed-effects in order to capture the impact of time-series differences in GDP growth on the likelihood that firms switch. In column 4 I do not use bank fixed-effects to capture the relationship between cross-sectional differences among banks and differences in the probability of switching. Columns 5 and 2 differ because in column 5 I use the probability of default as a measure of firm risk, while in column 2 I use bank relationship default dummies. I assume that $Prob.default = 100\%$ for firms that are contemporaneously defaulted to increase sample size.

Larger firms are more likely to switch banks. An increase of 1% in turnover is associated to an increase in the probability of switching of approximately 0.003 p.p. to 0.004 p.p. (approximately 0.3% over the unconditional monthly probability of switching of 1.17%). These results are consistent with findings

1. The period of analysis is limited by the availability of accounting information for firms.

Regression	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log turnover	0.207***	0.203***	0.202***	0.204***	0.194***
	[0.0030]	[0.0036]	[0.0036]	[0.0036]	[0.0038]
	(0.0074)	(0.0057)	(0.0058)	(0.0052)	(0.0055)
Age (years)	-0.0124***	-0.0130***	-0.0129***	-0.0127***	-0.0121***
	[-0.0002]	[-0.0002]	[-0.0002]	[-0.0002]	[-0.0002]
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Missing fields (%)	-2.476***	-2.368***	-2.557***	-2.510***	-1.400***
	[-0.0354]	[-0.0422]	[-0.0456]	[-0.0439]	[-0.0274]
	(0.200)	(0.135)	(0.143)	(0.131)	(0.0874)
Revenue growth (%)	0.308***	0.302***	0.304***	0.302***	0.307***
	[0.0044]	[0.0054]	[0.0054]	[0.0053]	[0.0060]
	(0.0069)	(0.0052)	(0.0052)	(0.0048)	(0.0079)
ROA (%)		-2.160***	-2.199***	-2.216***	-1.742***
		[-0.0385]	[-0.0392]	[-0.0388]	[-0.0341]
		(0.111)	(0.132)	(0.149)	(0.132)
Defaulted relationship	-0.0373*	0.0057	0.0013	0.0221	
	[-0.0005]	[0.0001]	[0.0000]	[0.0003]	
	(0.0215)	(0.0225)	(0.0226)	(0.0315)	
Prob. default					0.0072
					[0.0001]
					(0.0251)
Bank leverage (%)		0.0988***	0.0856***	0.110***	0.0378
		[0.0018]	[0.0015]	[0.0019]	[0.0007]
		(0.0220)	(0.0285)	(0.0277)	(0.0244)
# relationships	0.0354***	0.0285***	0.0283***	0.0321***	0.0220***
	[0.0005]	[0.0005]	[0.0005]	[0.0006]	[0.0004]
	(0.0080)	(0.0072)	(0.0072)	(0.0068)	(0.0066)
Rel. length (years)	0.0125***	0.0123***	0.0125***	0.0109***	0.0118***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
	(0.0024)	(0.0027)	(0.0027)	(0.0023)	(0.0028)
GDP growth (%*100)			0.0332***		
			[0.0006]		
			(0.0039)		
Log bank assets	0.0184	0.0270	-0.136	-0.0308	0.0311
	[0.0003]	[-0.0028]	[-0.0006]	[0.0005]	
	(0.0726)	(0.0845)	(0.0889)	(0.0209)	(0.0827)
Tier 1 (%)				-0.2605***	
				[0098]	
				(0.0831)	
Constant	-3.371***	-3.432***	-2.626***	-3.139***	-3.584***
	(0.443)	(0.524)	(0.563)	(0.215)	(0.516)
Observations	24,454,483	13,322,436	13,322,436	9,922,814	9,166,484
Date	Yes	Yes	No	Yes	Yes
Bank	Yes	Yes	Yes	No	Yes
Sector	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at the bank level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2. **Characteristics related to the probability of switching.** Logit marginal effects are reported in brackets and clustered standard errors at bank level in parentheses. I test whether coefficients are statistically significant at the 10%, 5%, and 1% levels using *, **, and ***, respectively. The unit of observation in this table is the number (n) of switching and nonswitching loans with monthly periodicity. Table A1 contains a list of variable meanings.

by Petersen and Rajan (1994) that small firms value more relationship banking than larger firms, even though the effect is small. Older firms are less likely to switch banks (-0.02 p.p. per additional year off age, or -1.7% over the unconditional probability of switching)

Opaqueness is negatively related with the probability that firms switch banks. According to Berger and Udell (1995) a nd Cole (1998) relationship banking is more valuable for opaque firms. In Portugal, an increase of one percentage point in the number of missing accounting fields is related to a decrease in the probability that firms switch banks of 0.03 to 0.04 percentage points (approximately a 3% decrease over the average unconditional probability of switching).

As described by Farinha and Santos (2002), high-growth firms are more likely to switch banks. One percentage point in revenue growth is related to an increase in the probability of switching between 0.004 and 0.006 percentage points (between 0.3% and 0.5% over the unconditional probability of switching).

Better performing firms are less likely to switch. An increase of 1 p.p. in ROA is associated to a decrease in the probability of switching of 0.03 to 0.04 p.p. (3% decrease over the average unconditional probability of switching).

Firms with higher probability of default or that are currently defaulting on the inside bank do not have significantly different probabilities of switching. Apparently, firms tend to switch if they have lower returns. However, objective indicators of default seem not to have a significant relationship with the probability that the firm switches banks.

Firms with longer bank relationships are more likely to switch, which gives support to the idea from Ongena and Smith (2001) that firms value less their bank relationships with time. Firms with more bank relationships are also more likely to switch banks, which is consistent with the hypothesis from Rajan (1992) that competition reduces the net present value of bank relationships for banks.

Evidence from Portugal is consistent with the hypothesis of Hale (2012) that firms are less likely to switch banks during downturns. I measure economic performance using the quarterly Portuguese real GDP growth. In column 3 I find that for an extra percentage point of GDP growth increases the probability that firms switch to a new bank by 0.06 percentage points (approximately 5% over the unconditional probability of switching).

Evidence for the impact of bank characteristics on the probability of switching is mixed. In column 2 I measure both the cross-sectional and the time series relationship between bank assets and Tier 1 ratio and the probability of switching. The relationship for bank assets is not significant, while firms are less likely to switch from banks with higher Tier 1 ratios. While evidence is consistent with the hypothesis from Gopalan *et al.* (2011) that firms are more likely to switch from banks with lower capacity to provide financing, size does not seem to have a significant impact on bank switching.

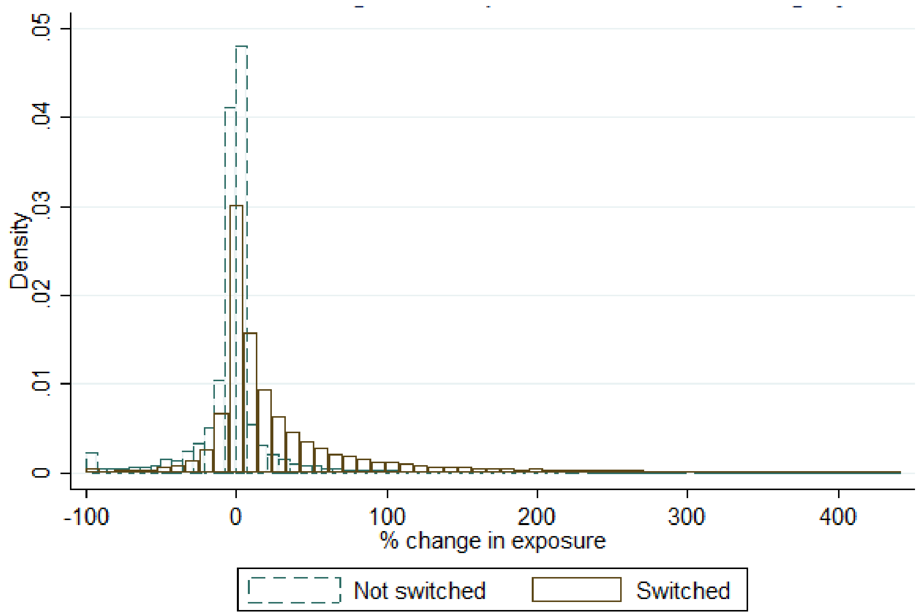

FIGURE 3: **Change in firm credit exposure for switchers and non-switchers.** Distribution of bank relationships according to change in exposure at month t. Switching relationships are represented by the solid line histogram and non-switching relationships by the dashed line histogram.

Switcher heterogeneity

Figure 3 shows the distribution of firms according to changes in their exposure to the banking system at month t for switchers and non-switchers. The distribution of the change in loan exposures for switching firms seems to be more skewed to the right than for non-switching firms. The median switching firm seems to be increasing their exposure more than the median non-switching firm. However, there is heterogeneity among switching firms.

In approximately 25% of all cases, firms' exposure to the banking system does not grow when firms switch banks. Potential amounts (i.e. lines of credit) count for the total exposure of banks to the financial system. Therefore, these cases are not necessarily originated by firms that establish new lines of credit but do not increase their actual volume of realized loans.

Table 3 summarizes the descriptive statistics for switching bank relationships, according to the variation in exposure at the time of the switching event. I calculate the change in bank exposure for all firms in the data set and derive four quantiles for these changes. I divide switching relationships according to the bank exposure quartile of the respective switching firm. Most firms are in the fourth quartile, which derives from the

	Q1		Q2		Q3		Q4	
	Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean
Firm characteristics								
Age (years)	40,975	16.2	63,374	16.2	23,890	16.6	260,284	14.6
Turnover (EUR million)	41,684	16.2	64,174	5.5	24,286	4.1	263,027	4.7
Opaqueness index (%)	41,684	9.6	64,174	9.1	24,286	9.3	263,027	9.8
Turnover growth (%)	37,988	6.8	58,650	4.6	20,532	1.4	235,510	8.3
ROA (%)	31,154	2.7	45,054	2.3	14,471	2.3	197,851	2.6
Bank leverage (%)	36,934	22.6	57,839	28.1	21,514	31.6	232,385	24.7
Prob. default (%)	26,376	4.2	39,968	5.0	12,321	5.5	172,435	4.5
Relationship characteristics								
Defaulting relationship (%)	43,431	6.2	67,171	9.0	30,099	32.5	276,530	7.0
Duration (years)	43,431	7.5	67,171	7.1	30,099	7.5	276,530	6.6
Number of relationships	43,431	3.2	67,171	3.5	30,099	3.2	276,530	3.0
Inside bank characteristics								
Bank assets (EUR Million)	43,368	53,472	67,066	50,366	30,061	52,043	275,994	51,688
Tier 1 Ratio (%)	31,698	8.3	47,854	8.3	21,635	8.5	199,434	8.5

TABLE 3. **Selected characteristics of switching relationships according to their firms' bank exposure quantile.** I report the mean for selected firm, relationship and bank characteristics. The unit of observation in this table is the number (n) of switching and nonswitching loans with monthly periodicity. I calculate the change in bank exposure for all firms in dataset and divide these firms in four quartiles. See table A1 for the meaning of each variable.

fact that switching firms tend to increase their bank exposures more than non-switching firms (see figure 3). In order to eliminate the impact of extreme outliers, I trim revenue growth, return on assets, and bank leverage at the 5% and 95% levels. I also trim firm age at the 99% level.

In table 4, I run specification (5) of table 2 for each quartile of table 3. For example, in regression Q1 the dependent variable is a dummy that is equal to 1 if I verify two conditions: first, the firm switches from a given bank relationship; second, the variation in total exposure of this firm to the banking system is within the first quartile of variation in bank exposure.

I perform this exercise to test whether switching firms have different characteristics according to their change in exposure to the financial system after they switch banks. Overall, results are similar among the four groups. Firms are more likely to switch if they are younger, have higher turnover, are less opaque, and are less profitable. However, firms are more likely to switch and belong to the fourth quartile of bank exposure if they have a lower probability of default, i.e. if they are less risky. For the second and third quartiles, firms are more likely to switch if they are riskier. These results mean that riskier firms that switch banks seem to not increase their exposure to the banking system significantly.

Regression	Q1	Q2	Q3	Q4
Age (years)	-0.0109***	-0.0064***	-0.0018	-0.015***
	[-0.0000]	[-0-.0000]	[0.0000]	[-0.0002]
	(0.0013)	(0.0010)	(0.0011)	(0.0009)
Log turnover	0.3307***	0.1953***	0.2424***	0.1651***
	[0.0007]	[0.0006]	[0.0002]	[0.0022]
	(.0048)	(0.0077)	(0.0076)	(0.0056)
Missing fields (%)	-0.4855**	-2.3832***	-0.8695***	-1.4166***
	[-0.0010]	[-0.0076]	[-0.0009]	[-0.0191]
	(.2001)	(0.1935)	(0.2785)	(0.0952)
Turnover growth (%)	0.2589***	0.0964***	-0.02024	0.3758***
	[0.0006]	[0.0003]	[-0.0000]	[0.0051]
	(0.0270)	(0.0199)	(0.0363)	(0.0098)
ROA (%)	-0.5068**	-3.4687***	-1.7769***	-1.6675***
	[-0.0011]	[-0.0111]	[-0.0018]	[-0.0225]
	(0.2312)	(0.2782)	(0.3503)	(0.1683)
Bank leverage (%)	-0.7772***	0.6797***	1.3122***	-0.0906***
	[-0.0017]	[0.0027]	[0.0013]	[-0.0012]
	(0.0741)	(0.0254)	(0.0922)	(0.0270)
Relationship length (years)	0.0149***	0.0135***	0.0089***	0.0107***
	[0.00003]	[0.00004]	[0.00000]	[0.00014]
	(0.0032)	(0.0022)	(0.0027)	(0.0030)
# relationships	-0.0056	0.0709***	-0.0154*	0.0161**
	[-0.0000]	[0.0002]	[-0.0000]	[0.0002]
	(0.0073)	(0.0054)	(0.0080)	(0.0073)
Log bank assets	-0.0080	0.0156	0.1362	0.0346
	[-0.0000]	[0.0001]	[0.0001]	[0.0005]
	(0.0651)	(0.1020)	(0.1251)	(0.0869)
Prob. default	-0.0463	0.3591***	1.3107***	-0.2749***
	[-0.0001]	[0.0012]	[0.0013]	[-0.0037]
	(0.0488)	(0.0309)	(0.0454)	(0.0272)
Observations	9,117,400	9,117,800	9,116,385	9,117,800
Date	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 4. **Characteristics related to the probability of switching for each exposure quantile.** Logit marginal effects are reported in brackets and clustered standard errors at bank level in parentheses. I test whether coefficients are statistically significant at the 10%, 5%, and 1% levels using *, **, and ***, respectively. Each regression corresponds to a quantile of change in total bank exposure of the firm, from the lowest quartile (Q1) to the highest quartile (Q4). The unit of observation in this table is the number (n) of switching and nonswitching loans with monthly periodicity. Table A1 contains a list of variable meanings.

Conclusion

In this article I review the literature about bank switching and analyze which factors affect bank switching in the Portuguese economy.

First, I define switching as establishing a new bank relationship for at least 12 months with a new bank that had no relationship with the firm. I call this bank the *outside bank*. I also require that the firm has at least one relationship with another bank for at least 12 months, which I call the *inside bank*. With this definition, I align the definition of switching with the previous literature about this topic. Additionally, with this definition I guarantee that firms do an active effort to establish a relationship with a different bank.

I review the literature about bank switching and describe which factors are related to the probability that a firm switches banks. At the macroeconomic level, firms are more likely to switch in growth periods. At the firm level, switching is more common for larger firms and more transparent firms, as size and transparency reduce the value of soft information between the bank and the firm. High-growth firms are more likely to switch, and according to the literature the costs of being held-up by the inside bank are higher for them. Firms with lower performance are also more likely to switch banks, as banks try to diversify the risk from lending to riskier firms. Previous literature also finds that switching is more likely if the inside bank is smaller. This happens because smaller banks do not have as much capacity to provide more loans to firms as larger banks. At the relationship level, according to previous literature the likelihood of switching should increase with the duration of the relationships, because firms value less relationships with time. According to the literature, firms are also more likely to switch if they have more bank relationships *ex-ante*.

I characterize bank switches in Portugal from 1981 to 2014 and find that between 1981 and 2008 the number of bank switches grew. I also find that after 2008 there was a drop in the number of switches and the percentage of firms that switch banks, which was aggravated in 2012.

I also regress the probability of switching on the macroeconomic, firm, bank, and firm-bank relationship characteristics mentioned in the literature. I find that in general in Portugal switching is related to the factors mentioned in the literature. Firms are less likely to switch banks during downturns. Larger, more transparent, and high-growth firms are more likely to switch. Firms with higher return on assets are less likely to switch. Firms that switch and do not increase their exposure to the banking system significantly seem to be riskier, while firms that switch and increase their exposure to the financial system tend to be less risky. Firms are more likely to switch from longer relationships or when they have a larger number of bank relationships. At the bank level, firms are more likely to switch from worse capitalized banks, but the effect of bank size on switching in not clear.

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Appendix

Variable	Unit	Description
Firm characteristics		
Age	Years	Company age
Turnover	EUR Million	Revenue from sales of services and goods
Opaqueness index	Percentage	Percentage of non-reported fields on Informação Empresarial Simplificada
Turnover growth	Percentage	Growth of revenue from sales of services and goods
ROA	Percentage	Profit over assets
Bank leverage	Percentage	Bank debt over assets
Probability of default	Percentage	Probability that the firm defaults in 1 year derived from accounting characteristics
Defaulting firm	Percentage	Firms that have loans overdue
Relationship characteristics		
Defaulting relationship	Percentage	Firm-bank relationships with amounts overdue
Duration	Years	Length of firm-bank relationship
Number of relationships	Units	Number of bank relationships the firm has
Bank characteristics		
Bank assets	EUR Million	Total bank assets
Tier 1 Ratio	Percentage	Tier 1 ratio of the bank
Controls		
Date	Categorical	Month of the firm-bank relationship (varies between 2006m1 and 2014m12)
Sector	Categorical	Sector of activity (agriculture, forestry and fishing, mining and quarrying, manufacturing, utilities, construction, wholesale and retail, transportation, hospitality and catering, financial services, professional services, other)

TABLE A1. Definition of variables used in the descriptive statistics and regressions.

Nowcasting Portuguese tourism exports

Sónia Cabral
Banco de Portugal

Cláudia Duarte
Banco de Portugal

October 2016

Abstract
Given the increasing importance of the continuous monitoring of economic activity, techniques that allow taking advantage of the timely releases of high-frequency data play a key role in short-term forecasting. This article compares two single-equation approaches, namely the traditional bridge models and the more recent Mixed Data Sampling (MIDAS) regressions, to nowcast Portuguese quarterly tourism exports. We consider different specifications of bridge and MIDAS models, as well as combinations of nowcasts, in a recursive pseudo real-time exercise. The evidence is in favour of using short-term indicators for nowcasting tourism exports. MIDAS regressions tend to outperform bridge equations, especially when less current-quarter information is available. The best results are always obtained from a combination of nowcasts from a MIDAS specification with autoregressive dynamics. (JEL: C53, F47, Z39)

Introduction

Travel is the most important sector in Portuguese international trade in services and it has been a major driver of the average surplus of the services account in the last two decades (Figure 1). Even if the importance of exports of other services has progressively risen over time, nominal travel exports still represented more than 45 per cent of total exports of services and more than 15 per cent of total Portuguese exports of goods and services in 2015. In addition, Portuguese exports of travel services have increased strongly in the last years, growing by around 50 per cent from 2010 to 2015. As a result, nominal travel exports represented 6.3 per cent of GDP in 2015 and the surplus of the travel account amounted to more than 4 per cent of GDP in 2015, the highest value of the last two decades.

Comparing with other European Union (EU) countries, the economic importance of the tourism sector for Portugal is also evident (Figure 2). The

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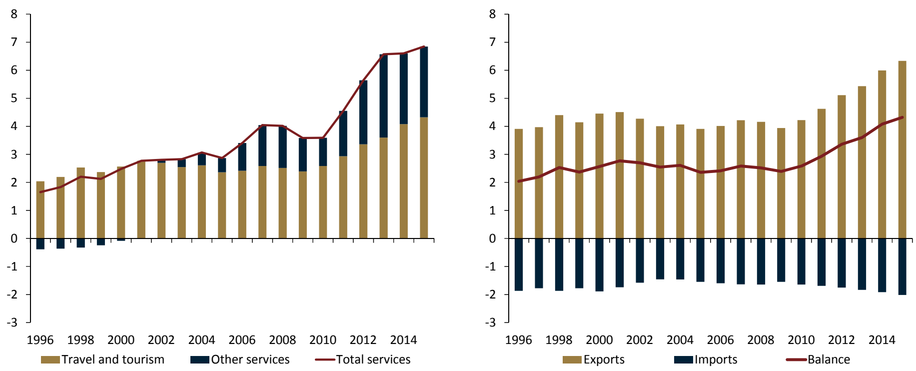


(A) Portuguese services account, balances (B) Portuguese travel account

FIGURE 1: Portuguese exports of tourism

Notes: Figures as a percentage of nominal GDP.
Sources: Statistics Portugal (INE) and Banco de Portugal.

ratio of Portuguese international tourism receipts to GDP increased from 4.8 per cent on average over the years 1995-2000 to 6.3 per cent in the period 2009-2014. This ratio of GDP is more than double the EU average and it is only surpassed by six other EU countries, most of them economies typically associated with significant tourism exports.

As tourism contributes significantly to the growth of the Portuguese economy, accurate forecasts of tourism demand are of particular importance. Calculating timely forecasts typically requires the identification of variables that not only bring useful information, but are also released early. The aim of this article is to use short-term monthly indicators to nowcast the real growth of tourism exports from Portuguese quarterly national accounts. The basic principle is to use information that is published early and at higher frequencies than the variable of interest in order to obtain projections before having observed data.

Considering that we are interested in projecting a quarterly variable on a monthly basis, nowcasting usually refers to the monthly projections of the current quarter and, hence, for each quarter, there are at least 3 different projections, one done in each month of the quarter. In this article, we define "nowcasting" as the projections of a quarter since the first month of that quarter until the official figures are released. Given that Portuguese quarterly national accounts are typically available 60 days after the end of the reference quarter, we produce 5 distinct nowcasts for each quarter. We have data from October 2000 to March 2016 and make use of reduced-form models in a pure time-series approach to nowcast inbound tourism in a recursive pseudo real-time exercise, which mimics the release pattern of the high-frequency

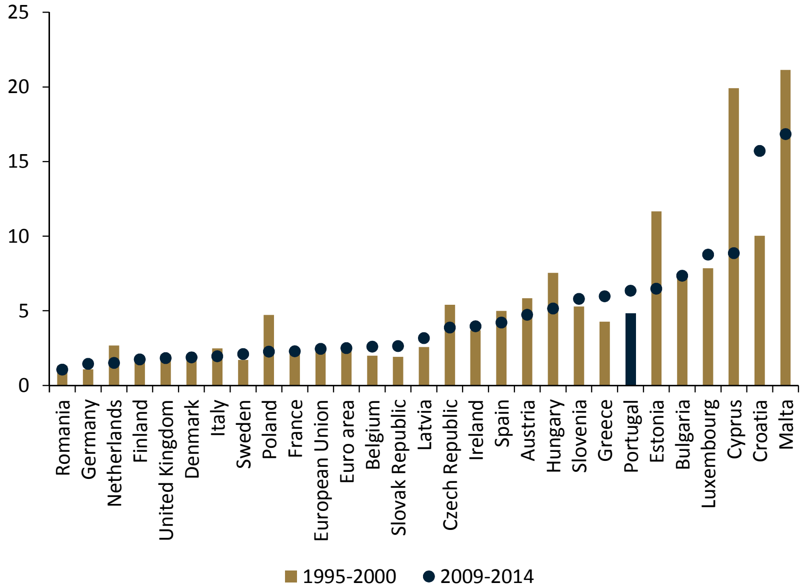


FIGURE 2: International tourism receipts

Notes: International tourism receipts, as percentage of GDP (current U.S. dollars). International tourism receipts are expenditures by international inbound visitors, including payments to national carriers for international transport. These receipts include any other prepayment made for goods or services received in the destination country.
Source: The World Bank - World Development Indicators (WDI).

indicators in real-time situations. The article goes beyond the traditional bridge equations and applies Mixed Data Sampling (MIDAS) regressions as proposed by Ghysels *et al.* (2007). Compared with other mixed-frequency models, the MIDAS approach is appealing because it is a simple, flexible and parsimonious single-regression framework. As far as we know, this is the first application of MIDAS regressions to short-term forecasting quarterly tourism exports.

The results obtained show that, in general, using short-term indicators to nowcast tourism exports is useful, as it delivers more accurate projections than those of a univariate benchmark throughout the whole period. MIDAS models tend to outperform the traditional bridge equations, especially when less current-quarter data on the indicators is available. Pooling nowcasts is a winning strategy for all mixed-frequency models considered: it allows improving on both univariate and single-indicator models. Considering all models and combinations of nowcasts, the best performing result in any period is always from a combination of nowcasts of a MIDAS model with autoregressive dynamics. Overall, despite the relatively short evaluation sample, we provide robust evidence on the improvement in the nowcast accuracy by pooling projections of MIDAS models.

The article is organised as follows. Section 2 discusses some of the related research that frames this study and highlights its main contributions to the literature. Section 3 briefly presents the bridge equations and the MIDAS regressions. Section 4 describes the variables and the design of the empirical exercise of nowcasting Portuguese exports of tourism. Section 5 discusses the results of the exercise conducted. Finally, section 6 presents some final remarks.

Related literature

Tourism demand modelling and forecasting has been an important area of research over the last decades and a number of new methods and techniques have emerged in the literature (see Song and Li (2008) for a survey of studies published after 2000). A special issue of the *International Journal of Forecasting* provides a useful and detailed description of recent developments in tourism forecasting (see Song and Hyndman (2011) for an introduction to this special issue and the papers therein). The review of the vast empirical literature on tourism modelling and forecasting is beyond the scope of this article. Instead, this section offers a non-exhaustive list of references in different strands of the literature that are related to our study and provide a framework for our analysis, with a special focus on the Portuguese economy.

In general, the tourism forecasting literature is still dominated by two main methods: non-causal time-series models and causal econometric approaches. Our study fits in the former broad category. Athanasopoulos *et al.* (2011) conclude that pure time-series approaches forecast tourism demand data more accurately than alternative methods. However, this finding is not unanimous in the literature, as there are numerous conflicting results, especially when using more sophisticated causal models (see, for instance, Song *et al.* (2011)).

Within the time-series models, our work contributes to the general study of tourism activities in Portugal. Given the relevance of the tourism sector, there are some research and policy oriented studies in this area focusing on the Portuguese economy. However, the literature on Portuguese international trade in tourism services is still limited when compared with the large number of studies on Portuguese international trade in goods. Some notable exceptions are Daniel and Ramos (2002) that perform an econometric analysis of the number of tourists arriving from five different origins using cointegration and error correction methods and Teixeira and Fernandes (2012, 2014) that use artificial neural networks models to forecast Portuguese tourism revenues and overnights. Using monthly data on tourist overnight stays in hotel accommodations, Gouveia and Rodrigues (2005) apply a nonparametric method to identify tourism growth cycles, concluding that there is a time lag between tourism demand cycles and economic cycles and Rodrigues and Gouveia (2004) use a parsimonious periodic autoregressive model and demonstrate its superiority in forecasting performance compared to other models. Andraz *et al.* (2009) use a diffusion index model for forecasting tourism demand in Algarve from the UK and confirm its better forecasting performance. More recently, Serra *et al.* (2014) use dynamic panel data models to model international tourism demand in seven different Portuguese tourist regions, finding a heterogeneous behaviour by region.

In our case, we focus on nowcasting developments in quarterly exports of tourism, in real terms. Hence, our article is also related to a large empirical literature on short-term forecasting of economic variables, and in particular, on forecasting Portuguese demand-side components of GDP. In this context, bridge equations are one of the most commonly used techniques to deal with mixed-frequency datasets. Typically, they link monthly and quarterly variables that show a significant correlation and the choice of the regressors tends to take into account their timeliness (see, for instance, Baffigi *et al.* (2004)). Esteves and Rua (2012) provide a general description of the methodology of the short-term forecasting exercise of the Banco de Portugal, where bridge models are the preferred modelling tool. Other applications of bridge models in the short-term forecasting exercises of the Portuguese economy include Cardoso and Duarte (2006) for exports of goods, Maria and Serra (2008) for investment and Esteves (2009) for private consumption.

In addition to the traditional bridge model approach, we consider MIDAS regressions. By using this technique, our article also contributes to a recent stream of empirical literature that uses MIDAS models for handling different sampling frequencies and asynchronous releases of information. Inspired in the distributed lag models, MIDAS regressions are very flexible, being able to account for different frequencies, different aggregation polynomials and different forecast horizons (for a brief overview of the main topics related with MIDAS modelling, see Andreou *et al.* 2011). Recently, Duarte *et al.* (2016) use MIDAS models for nowcasting and forecasting quarterly private consumption in Portugal. As far as we know, the MIDAS approach has not been applied to short-term forecast quarterly tourism exports yet and this article aims at filling that gap.

Bridge equations and MIDAS regressions

Early information on the state of the economy is crucial for policy-making. However, important official statistics, such as those of national accounts, are only available on a quarterly basis and with relevant publication delays. For example, the flash estimate for Portuguese GDP is available 45 days after the end of the quarter, while the main aggregates on the expenditure side are available 60 days after the end of the reference quarter. In this context, techniques for dealing with mixed-frequency data are useful tools to take advantage of the large number of relevant short-term indicators, allowing a timely evaluation of the current economic situation. Several types of econometric tools to combine data with different frequencies and exploit early releases of high-frequency data for improving forecast accuracy have been proposed in the literature; Foroni and Marcellino (2014) briefly describe the main approaches. This section focuses on two specific econometric approaches, which deal with mixed-frequency data in a simple and appealing way: bridge equations and MIDAS regressions (see, for instance, Schumacher (2016) for a recent comparison of these models).

Bridge equations

Bridge equations are one of the most commonly used techniques to link data with different time frequencies. Typically, the series with higher time frequency are, first, aggregated to the (lower) frequency of the dependent variable and, then, included in traditional forecasting models. These models have been widely considered in the literature, especially to forecast GDP growth in national and international institutions (e.g., Baffigi *et al.* 2004, Diron 2008, Barhoumi *et al.* 2012 and Bulligan *et al.* 2015).

Considering y_t sampled at a quarterly frequency (interval of reference) as the dependent variable, the specification of a simple bridge equation with a single indicator and autoregressive terms is given by:

$$y_{t+h} = \beta_0 + \beta(L)x_t^Q + \gamma(L)y_t + \varepsilon_{t+h}, \tag{1}$$

where the predictor x_t^Q is a quarterly variable obtained by aggregating its high-frequency counterpart $x_t^{(m)}$ sampled m times faster (for example, for monthly data m equals 3), h is the quarterly horizon, and ε_{t+h} is a standard i.i.d. error term. The quarterly lag polynomial $\beta(L)$ of order k is defined as $\beta(L) = \sum_{i=0}^{k} \beta_{i+1}L^i$, with $Lx_t^Q = x_{t-1}^Q$. Similarly, $\gamma(L)$ is a p-order polynomial in the lag operator defined as $\gamma(L) = \sum_{i=1}^{p} \gamma_i L^i$, where p is the number of autoregressive terms and $Ly_t = y_{t-1}$. Equation 1 can be easily extended to a multivariate format simply by including additional regressors and each one can have a distinct $\beta(L)$ polynomial.

Depending on the data release lags, the high-frequency indicators may need to be extended with estimates, before being temporally aggregated and included in the bridge model. Considering quarterly and monthly data, estimates for the missing monthly observations, obtained from simple univariate models, are plugged in the monthly data, which are transformed into quarterly series and, then, used for forecasting in the quarterly bridge model.

MIDAS regressions

This section gives a brief overview of the MIDAS regressions used in this article. Armesto *et al.* (2010) provide a simple and a intuitive introduction to the subject and comprehensive discussions of MIDAS regression for short-term forecasting can be found in Andreou *et al.* (2011), Foroni and Marcellino (2014), Schumacher (2016) and references therein. Finally, a recent annals issue of the *Journal of Econometrics* (Ghysels and Marcellino 2016) discusses in detail several econometric methods designed to handle mixed-frequency data.

The MIDAS regressions, introduced by Ghysels *et al.* (2004), are a direct multi-step forecasting tool inspired in the distributed lag models. In addition, as discussed in Duarte (2014), an autoregressive term can simply be added to the MIDAS equation. Consider again y_t sampled at a quarterly frequency and $x_t^{(m)}$ sampled m times faster. A simple MIDAS regression with autoregressive terms is:

$$y_{t+h} = \beta_0 + \beta_1 B(L^{1/m};\theta)x_t^{(m)} + \gamma(L)y_t + \varepsilon_{t+h}, \tag{2}$$

where h is the quarterly horizon, $B(L^{1/m};\theta) = \sum_{j=0}^{jmax} B(j;\theta)L^{j/m}$ is a polynomial of length $jmax$ in the $L^{1/m}$ operator, $B(j;\theta)$ represents the weighting scheme used for the aggregation, which is assumed to be normalised to 1, $L^{j/m}x_t^{(m)} = x_{t-j/m}^{(m)}$, and ε_{t+h} is a standard i.i.d. error term.

Although the order of the polynomial $B(L^{1/m};\theta)$ is potentially infinite, some restrictions must be imposed for the sake of tractability. In a MIDAS regression, the coefficients of $B(L^{1/m};\theta)$ are captured by a known weighting function $B(j;\theta)$, which depends on a few parameters summarized in vector θ. MIDAS models are, thus, tightly parameterised, which is one of the key features of this technique.

Some alternatives for the weighting function have been suggested in the literature; see, namely, Ghysels *et al.* (2007). The most commonly used polynomial is the exponential Almon lag polynomial:

$$B(k;\theta_1,\theta_2) := \frac{e^{(\theta_1 k + \theta_2 k^2)}}{\sum_{k=1}^{K} e^{(\theta_1 k + \theta_2 k^2)}}, \tag{3}$$

where $f(q,\theta_1,\theta_2) = (q^{\theta_1 - 1}(1-q)^{\theta_2 - 1}\Gamma(\theta_1+\theta_2))/(\Gamma(\theta_1)\Gamma(\theta_2))$ and $\Gamma(\theta) = \int_0^\infty e^{-k}k^{\theta-1}dk$. Since the exponential Almon polynomial has a nonlinear functional specification, MIDAS regressions have to be estimated using nonlinear methods, namely nonlinear least squares.

A MIDAS variant discussed by Chen and Ghysels (2011) is the multiplicative MIDAS (M-MIDAS), which is closer to traditional aggregation schemes. Instead of aggregating all lags in the high-frequency variable to a single aggregate, multiplicative MIDAS models include m aggregates of high-frequency data and their lags, i.e.,

$$y_{t+h} = \beta_0 + \sum_{i=1}^{p} \beta_i x_{t-i+1}^{mult} + \gamma(L) y_t + \varepsilon_{t+h}, \quad (4)$$

where $x_t^{mult} = \sum_{j=0}^{m-1} B(j;\theta) L^{j/m} x_t^{(m)}$.

A different MIDAS approach is the unrestricted MIDAS (U-MIDAS) regression proposed by Foroni *et al.* (2015):

$$\begin{aligned} y_{t+h} &= \beta_0 + B_u(L^{1/m}) x_t^{(m)} + \gamma(L) y_t + \varepsilon_{t+h} \\ &= \beta_0 + \sum_{j=0}^{J} \beta_{j+1} L^{j/m} x_t^{(m)} + \gamma(L) y_t + \varepsilon_{t+h} \\ &= \beta_0 + \beta_1 x_t^{(m)} + \beta_2 x_{t-1/m}^{(m)} + \ldots + \beta_{J+1} x_{t-J/m}^{(m)} + \gamma(L) y_t + \varepsilon_{t+h}. \quad (5) \end{aligned}$$

The U-MIDAS regression does not resort to functionals of distributed lag polynomials and, hence, has the advantage that it can be estimated by OLS. However, given the parameter proliferation, the U-MIDAS models are better able to deal with monthly data, than weekly or daily data, as large differences in sampling frequencies between the variables considered are very penalised in terms of parsimony.

Finally, Clements and Galvão (2008) suggested an alternative way of introducing autoregressive dynamics in MIDAS regressions. The authors proposed interpreting the dynamics on y_t as a common factor, resting on the hypothesis that y_{t+h} and $x_t^{(m)}$ share the same autoregressive dynamics. Consider a simple MIDAS regression where the error term can be represented by an autoregressive model of order 1. The common factor MIDAS (CF-MIDAS) model can be written as:

$$(1 - \gamma L) y_t = \beta_0(1 - \gamma) + \beta_1(1 - \gamma L) B(L^{1/m};\theta) x_t^{(m)} + \varepsilon_t. \quad (6)$$

Although the initial work by Clements and Galvão (2008) only considers a single autoregressive term, it is possible to extend this technique to allow for more autoregressive terms.

In summary, MIDAS models have a more flexible weighting structure than traditional low-frequency models and tend to be more parsimonious. The MIDAS framework can also easily accommodate the timely releases of high-frequency data. In equation 2, it is assumed that all high-frequency observations of $x_t^{(m)}$ over the low-frequency period of reference are known. Considering quarterly and monthly data, this means that the three months of information on the quarter of interest are already available for the short-term indicator. If instead of a full-quarter of data, only, say, the first month is available, then the MIDAS regression can be written as:

$$y_{t+h} = \beta_0 + \beta_1 B(L^{1/3};\theta)x^{(3)}_{t-2/3} + \gamma(L)y_t + \varepsilon_{t+h}. \qquad (7)$$

Furthermore, MIDAS regressions can be extended to accommodate additional high-frequency indicators, and, in some cases, without requiring many more parameters to be estimated. Moreover, different polynomials $B(L^{1/m};\theta)$ for each regressor can also be considered.

Data and design of the exercise

Data

The dependent variable is tourism exports from the Portuguese quarterly national accounts at constant prices and seasonally and calendar effects adjusted. Throughout this article, tourism exports refer to the System of National Accounts concept of household final consumption expenditure of tourism of non-resident visitors in Portugal, and does not include the intermediate tourism consumption associated with business travels of non-residents.[1]

Four types of short-term variables related to tourism exports are published monthly and, hence, were the basis of the four individual indicators included in the exercise to nowcast quarterly tourism exports.

Firstly, we use the nominal exports (credits) from the travel account of the Portuguese Balance of Payments (BoP) deflated with the total Harmonised Index of Consumer Prices (HICP).[2]

Secondly, we consider the transactions with cards issued abroad in terminals located in Portugal (ATM/POS). These transactions include both Automated Teller Machines (ATM) cash withdrawals and Points of Sale (POS) transactions and are available since September 2000. The values of the monthly ATM/POS transactions were deflated using the total HICP.[3]

Thirdly, another indicator is the number of non-resident overnight stays in hotel establishments in Portugal. To account for potential quality effects,

1. The detailed data on tourism exports was kindly provided by Statistics Portugal (INE - `http://ine.pt/`).

2. Two other deflators were also tested to price-adjust BoP data. First, the HICP for the services aggregate was used. Second, a composite deflator was built by weighting several price components by their share in the expenditure of tourists in Portugal. We opted for using total HICP, which had the best performance, but the results do not qualitatively change with the two alternative deflators.

3. Similarly to nominal tourism exports from the travel account, we also considered two alternative deflators for the ATM/POS transactions (see footnote 2 for details) and the results remained broadly unchanged.

the number of overnight stays in each type of accommodation establishment was weighted by the respective average total income in the previous year. Five different individual types of hotel establishments (hotels, lodging houses, apartment hotels, tourist villages, tourist apartments) and a residual category (including boarding houses, inns and motels) were considered.[4]

Finally, we calculate a composite index of consumer sentiment in some of the main origin countries of tourists - Spain, the United Kingdom, France, Germany, Italy and the Netherlands. Surveys are particularly valuable because of their timeliness: they are the first monthly releases relating to the current quarter. The monthly consumer confidence indicator of each country published by the Directorate General for Economic and Financial Affairs (DG ECFIN) of the European Commission was weighted by the its importance as an origin of non-resident overnight stays in Portugal in the previous year.[5]

When needed, monthly series were seasonally and calendar effects adjusted. We applied the same procedure used by Statistics Portugal for seasonally adjusting monthly official statistics, namely the X-13 ARIMA with calendar effects adjustment resorting to JDemetra+ software provided by Eurostat. The sample period starts in the October 2000, which corresponds to the first month of the first quarter for which ATM/POS transactions are available, and ends in March 2016. With the exception of the confidence indicator, the original series were transformed to their year-on-year rate of change. In the case of the confidence indicator, absolute differences relative to the same period in the previous year were used.

Design of the exercise

The aim of this article is to nowcast the quarterly growth of Portuguese real tourism exports using four different monthly indicators. For that, we implement a pseudo real-time recursive and direct multi-step exercise with the following features.

All bridge and MIDAS models were recursively estimated with an expanding window and selected using the Bayesian Information Criterion (BIC). Starting from the initial in-sample period (from $2000Q4$ to $2007Q4$) that was used to specify the models, the estimation sample is expanded by adding a new observation in each round. [6] As a new observation is added to the sample, all models are re-estimated and, thus, the coefficients are allowed

4. We also experimented with the raw data on total non-resident overnight stays, but the nowcasting performance was not better.

5. We also used the standard consumer confidence indicators for both the EU and the euro area published monthly by the DG ECFIN and the results were qualitatively similar.

6. We also tested a rolling window and the main results regarding the differences between bridge and MIDAS models do not differ much.

to change over time. Regarding the out-of-sample nowcasting exercise, the evaluation sample covers the period from $2008Q1$ to $2016Q1$.

Different lags were used (up to 3 quarters), also for the autoregressive terms. MIDAS models were estimated using the exponential Almon polynomial defined in equation 3.[7] Bridge equations and the different MIDAS models described in section 3 were estimated with and without autoregressive terms.

An adequate selection of the predictors is crucial for obtaining the best forecast results over the periods considered. Given that in our case the information set comprises a small number of variables, we considered both single- and multi-variable models. In addition, we also tried a different strategy that can improve forecasting accuracy: pooling forecasts. Different pooling techniques are available in the literature, ranging from simple equal (and constant) weights to performance based weights. As simple combination schemes often show good performances, in this article two different pooling techniques are used: the equal-weight mean and the discounted mean squared forecast error (MSFE) combination proposed by Stock and Watson (2004). The Stock and Watson (2004) weights are as follows:

$$w_{it} = \frac{m_{it}^{-1}}{\sum_{i=1}^{n} m_{it}^{-1}} \qquad m_{it} = \sum_{s=t_0}^{T} \delta^{T-s}(y_s - \hat{y}_s^i)^2, \tag{8}$$

where $\hat{y}^i$ are the forecasts from model i and δ is the discount coefficient. The weights of this pooling technique depend inversely on the historical forecasting performance of each model. So, the greater the MSFE of an individual forecast, the smaller the associated weight.[8]

The dataset is a final vintage dataset, meaning that it refers to the latest release available when the database was built. In the case of the consumer confidence indicators and ATM/POS transactions final data equal real-time data, as these series are typically not revised. The revisions to BoP exports, overnight stays and quarterly tourism exports are not taken into account in this analysis but they are usually relatively small in Portugal, so the impact should be minor.

The existence of asynchronous release schedules of high-frequency series implies unbalanced panels with different patterns of missing values in the end of the sample (the so-called "ragged-edge" problem). There is evidence in the literature that accounting for this ragged-edge structure of the dataset can have a considerable impact in nowcast accuracy (see, for instance, Giannone *et al.* (2008)). Hence, we take into account this important characteristic of

7. The traditional Almon lag polynomial was also tested as an alternative for the weighting function. However, it did not improve the performance of the models.

8. Regarding the discount parameter, different values were considered and the non-discounting option ($\delta = 1$) showed the best results.

macroeconomic data in real-time. Following Foroni and Marcellino (2014) and Schumacher (2016), our pseudo real-time exercise mimics the release pattern of the indicators as they become available in real-time situations. More specifically, we replicate the unbalanced structure of the dataset in each of the recursive sub-samples, following a stylised publication calendar: for each series, we observe the number of missing values at the end and impose the same number of missing observations at each recursion.

As discussed in Banbura *et al.* (2011), one important feature of a nowcasting exercise is that one rarely performs a single projection for a given quarter but rather a sequence of nowcasts that are updated as new data arrive. Hence, considering forecasts of quarterly variables on a monthly basis, typically nowcasting refers to the monthly projections of the current quarter and there are at least 3 different projections for that quarter (one in each month of the quarter). However, by taking into account the publication delays of the variable of interest, it is possible to increase the number of projections before there is observed data. For example, Banbura *et al.* (2013) produce nowcasts of US GDP starting in the first month of the current quarter up to the first month of the following quarter, when the official data is published.

In our exercise, we also share this broader perspective about nowcasting. Hence, from the end of the first month of quarter t to the end of the second month of quarter $t+1$, when the official data is observed, it is possible to have up to 5 different nowcasts for quarter t, depending on the information set and the amount of within-quarter data available for each predictor. Given that all monthly indicators are typically observed before the release day of Portuguese quarterly national accounts (recall that the publication delay of expenditure-side aggregates is 60 days after the end of the reference quarter), in the months of their publication, i.e., February, May, August and November, we can obtain an early estimate for tourism exports before the official figure becomes available.

A simple example can help clarifying the structure of the dataset in our pseudo real-time exercise. Assume that one is interested in obtaining a projection of the real growth of Portuguese tourism exports in the first quarter of 2016. In the end of January 2016 (1st m Qt), the consumer confidence indicator is available for January but there is no current quarter information for the other variables: the ATM/POS transactions is available for December 2015 and both BoP exports and overnight stays are available for November 2015. A month later, in the end of February (2nd m Qt), there are two months of current quarter information for the consumer confidence indicator, data for the ATM/POS transactions is available for January, and there is still no current quarter data for the other two variables: both BoP exports and overnight stays are available for December 2015. Again, a month later, in the end of March (3rd m Qt) there are three months of current quarter data for the consumer confidence indicator, two months of data for the ATM/POS transactions and information for both BoP exports and overnight stays is available for January. In addition, from this date onwards, data on quarterly tourism exports for the fourth quarter of 2015 can also be included. In the end of April 2016 (1st m Qt+1), both the consumer confidence indicator and the ATM/POS transactions have three months of data of the quarter of interest and information for BoP exports and overnight stays is available until February. Finally, in the end of May (2nd m Qt+1), full-quarter information for all variables is observed.

In this example, the last two projections are performed in April and May 2016 and refer to the previous quarter. Note that, in contrast with our broad perspective on the term "nowcasting", which allows us to simplify the wording, in some applications, current and previous quarter forecasts are labelled as "nowcasts" and "backcasts", respectively (see Banbura *et al.* (2011)).

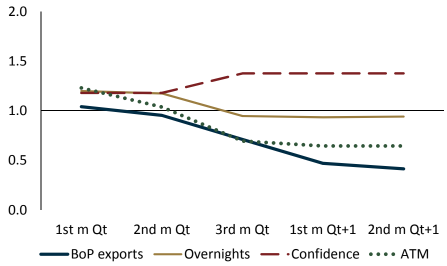
As using full-quarter data for all indicators allows having nowcasts for the growth of Portuguese tourism exports in a given quarter only a couple days before the release of the official GDP figures, it is essential to have projections that exploit partial within-quarter information much earlier than that. In the bridge model framework, when not all months of the quarter are available for the predictors, estimates for the missing monthly observations obtained from simple univariate models are used, as described in section 3. All nowcasts are computed directly, i.e., no projections of the dependent variable are used in order to obtain the nowcasts, which implies different bridge models for each quarterly horizon. In the MIDAS framework, the different nowcasts for the quarter of interest are computed using distinct models for each within-quarter information set of the variables, i.e., a new regression is used as new (monthly and quarterly) information is included.

Finally, to evaluate the nowcasting performance of the different bridge and MIDAS models in the out-of-sample period, we used the root mean squared forecast error (RMSE). Relative RMSE are computed to compare the performance of these two approaches with a quarterly benchmark model. The benchmark model is a univariate autoregressive (AR) model, which is estimated recursively, and the lag length (from 0 to 3 lags) is chosen according to the BIC.

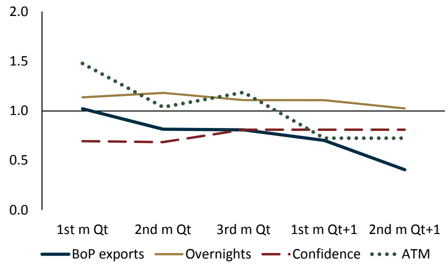
Main results

This section presents the results of the pseudo real-time nowcast exercise. As, on average, MIDAS models with AR dynamics outperformed MIDAS regressions without them throughout the whole evaluation periods, in what follows we focus only in the former MIDAS specifications. This finding is in line with other studies that showed that the MIDAS models without an AR component generally perform worse than the MIDAS specifications that include it (see, for instance, Kuzin *et al.* (2011) and Duarte (2014)). In addition, CF-MIDAS regressions were the worst models in terms of nowcast accuracy, so we also excluded them from the analysis.[9]

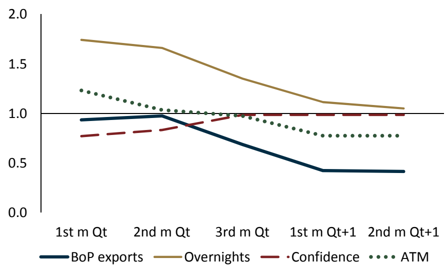
Regarding the results for single-variable regressions, Figure 3 provides evidence on the performances of the different classes of mixed-frequency models. The figures show the relative RMSE performances, at the different nowcast periods, against an AR benchmark. A ratio lower than 1 denotes a forecasting gain by the bridge and/or MIDAS approaches, whereas a value higher than 1 means that the univariate model outperforms the alternative models. Figure 3 shows heuristically one of the stylised facts of this literature: forecasting accuracy of this type of models tends to increase as time goes by and more information becomes available.



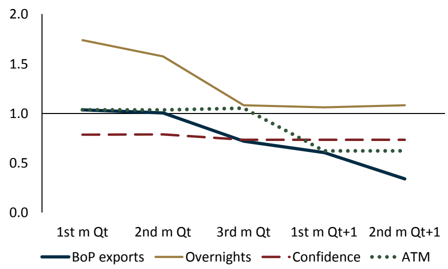
(A) Bridge equations



(B) AR-MIDAS regressions



(C) AR-U-MIDAS regressions



(D) AR-M-MIDAS regressions

FIGURE 3: Relative RMSE of single-variable models (benchmark = AR)

Notes: See Section 4 for a detailed description of the variables and the information used for each nowcast. Ratios of the RMSE with respect to an AR model. A ratio lower than 1 denotes a forecasting gain by the bridge and/or MIDAS models, whereas a value higher than 1 means that the univariate benchmark model outperforms the alternative models.

Starting with bridge equations, in the first two months of the reference quarter, no indicator outperforms the AR benchmark, but, as more data on the quarter is observed, taking into account exports from the BoP travel account,

9. All results are available from the authors upon request.

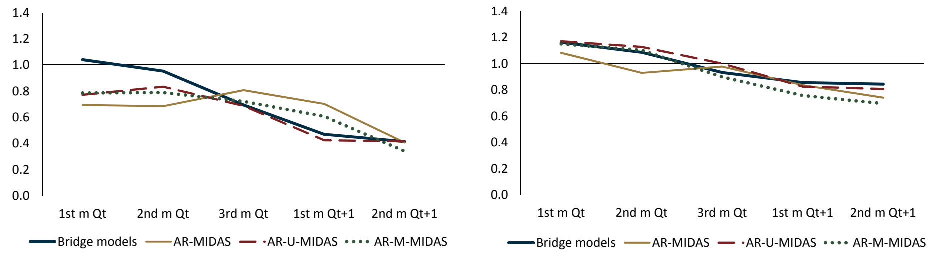
ATM/POS transactions and, to a lesser extent, overnight stays leads to a RMSE lower than the univariate benchmark in next three evaluation periods. Exports from the BoP travel account are the best indicator in all cases but one: the exception are ATM/POS transactions in the third month of the reference quarter, when there is only one month of BoP exports data, but two months information on ATM/POS transactions.

In contrast, the most accurate MIDAS regressions always outperform the AR benchmark throughout the evaluation periods. Focusing on the short-term indicators, there is a common pattern across the different MIDAS variants: in the first two months of the reference quarter, the best performing indicator is the consumer confidence index; henceforth, BoP exports have the best performance, as more data on this indicator for the reference quarter gradually becomes available. Moreover, the overnight stays variable tends to perform badly in MIDAS models, being worse than the AR benchmark in all cases.

In order to better investigate their properties and capture their differences and similarities over the whole set of individual indicators, Figure 4 provides evidence on the minima and average relative RMSE performances (against an AR benchmark) of the different classes of mixed-frequency models considered. Overall, the best performing model is always MIDAS, i.e., the MIDAS variant with the lowest RMSE always outperforms bridge models and this is true for both minima and average performances. However, in both cases, the best performing MIDAS model is not always the same variant.

Focusing on the minimum relative RMSE, the best nowcasting performance of a MIDAS model is always better than the AR benchmark and allows for gains from around 30 to 65 per cent throughout the whole period. In fact, compared to bridge equations, MIDAS regressions seem to work particularly well for short-term horizons, i.e., when less current-quarter information is available. In contrast, the lack of current-quarter data on BoP exports in the first two evaluation periods is critical for the performance of bridge equations, which never do better than the AR benchmark. In the last three evaluation periods, there are only mild differences between the MIDAS regressions with the lowest relative RMSE and the bridge model. In both cases, the nowcasting gains relatively to the univariate benchmark increase from around 30 per cent to about 60 percent in the last period.

Regarding the average nowcasting performances, it is difficult to outperform the AR benchmark in the first two months of the quarter (the only exception is the AR-MIDAS models in the second period). Moreover, there are no substantial differences between the average performances of the single-variable approaches over the whole period, even if the best MIDAS models perform (slightly) better, on average, than bridge equations in all periods.



(A) Minima performances

(B) Average performance

FIGURE 4: Minima and average relative RMSE of single-variable models (benchmark = AR)

Notes: See Section 4 for a detailed description of the information used for each nowcast. Minima and average of the relative RMSE ratios with respect to an AR benchmark within a model class across all indicators. A ratio lower than 1 denotes a forecasting gain by the bridge and/or MIDAS models, whereas a value higher than 1 means that the univariate benchmark model outperforms the alternative models.

Nowcast pooling

This section examines the results of the nowcast pooling exercise within each class of models. The combination of individual projections described in equation 8 has a better overall performance than multi-variable models and that the simple equal-weight mean of nowcasts. Hence, we will only analyse the results of the combination of nowcasts using the Stock and Watson (2004) weights.

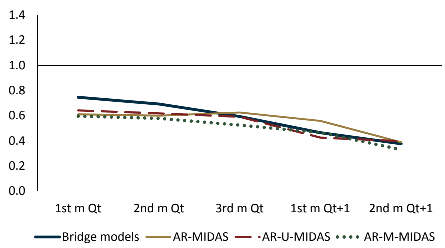
Figure 5 depicts the minima and average relative RMSE performances of the different models against an AR benchmark, considering all possible combinations of the four single indicators within each model. [10]

Comparing the results included in Figures 4 and 5, it is clear that nowcast pooling is a winning strategy that tends to outperform single-variable models for every period and type of model considered. The finding that pooling of nowcasts is more stable than nowcasting with single models is in line with other studies in the MIDAS literature. Kuzin *et al.* (2013) concluded that pooling outperforms single-variable models for nowcasting quarterly GDP growth and Ghysels and Ozkan (2015) showed that forecast combinations of MIDAS regression models provide gains over traditional models for forecasting the US annual federal budget. Moreover, Clements and Galvão

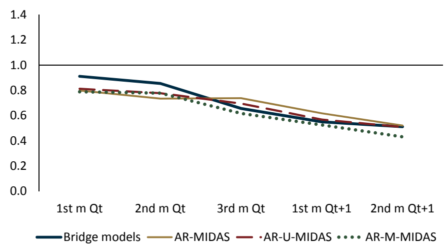
10. Appendix A includes the detailed results of the nowcast accuracy of the eleven possible combinations for all mixed-frequency models considered: the first table reports the relative RMSE performances of each model against the AR benchmark and the second table includes the RMSE performances of the different MIDAS variants relative to the RMSE of the bridge equations for each combination of predictors.

(2008) found that combinations of MIDAS forecasts are at least as good as combinations of forecasts from bridge models and other mixed-frequency models.

The relative RMSE of pooled nowcasts are always lower than 1 in all cases depicted in Figure 5, implying that not only the best model in each class performs better than the AR benchmark but also that, on average, it is possible to improve nowcasting accuracy by using mixed-frequency models. As in the single-variable models, the best performing model is always a MIDAS regression, both in terms of minima and average performances. Even if the best results are not always obtained from the same type of MIDAS model, the AR-M-MIDAS model delivers good nowcasting results throughout the whole period.



(A) Minima performances



(B) Average performance

FIGURE 5: Minima and average relative RMSE of nowcast pooling (benchmark = AR)

Notes: See Section 4 for a detailed description of the information used for each nowcast. Minima and average of the relative RMSE ratios with respect to an AR benchmark within a model class across all possible combinations of indicators. A ratio lower than 1 denotes a forecasting gain by the bridge and/or MIDAS models, whereas a value higher than 1 means that the univariate benchmark model outperforms the alternative models.

To examine in more detail the performance of nowcast pooling of the different models, Table 1 compares their relative RMSE performances against an AR benchmark. From the eleven possible combinations presented in Appendix A, this table shows the best performing ones for any given bridge/MIDAS model in each evaluation period. Following Foroni and Marcellino (2014), we test the hypothesis of equal accuracy in forecast performance using the Diebold and Mariano (1995) test modified for short samples by Harvey *et al.* (1997). The cases in which the hypothesis of equal forecast accuracy is rejected according to this test are indicated by one of more $*$ in the table, depending on the significance level.

The results show that nowcast pooling of both bridge and MIDAS models performs fairly well: it outperforms the AR benchmark for most of the combinations in each period and the differences in terms of RMSE are, in the vast majority of cases, statistically significant. For instance, in the last

	1st m Qt		2nd m Qt		3rd m Qt		1st m Qt+1		2nd m Qt+1	
Bridge models										
Overnights + Confidence	0.861		0.845		0.755	*	0.769	*	0.786	
ATM + Confidence	0.754	*	0.727		0.623	***	0.599	***	0.599	***
BoP exports + Confidence	**0.745**	*	**0.691**	**	0.694	**	0.493	***	0.450	***
BoP exports + Overnights	1.046		0.981		0.672	***	**0.464**	***	**0.376**	***
BoP exports + Overnights + Confidence	0.805	*	0.762	**	0.633	**	0.473	***	0.406	***
BoP exports + Confidence + ATM	0.794	*	0.747	**	**0.592**	***	0.483	***	0.435	***
BoP exports + Overnights + Confidence + ATM	0.848	*	0.802	**	0.604	***	0.488	***	0.427	***
AR-MIDAS										
Overnights + Confidence	0.611	**	**0.599**	**	0.656	**	0.655	**	0.738	*
ATM + Confidence	**0.609**	**	0.604	**	0.657	**	0.614	**	0.614	**
BoP exports + Confidence	0.683	**	0.631	**	0.662	**	0.662	**	0.433	***
BoP exports + Overnights	0.995		0.822	**	0.770	**	0.574	***	**0.388**	***
BoP exports + Overnights + Confidence	0.668	**	0.613	***	**0.624**	***	0.569	***	0.422	***
BoP exports + Confidence + ATM	0.657	**	0.624	***	0.637	***	0.561	***	0.434	***
BoP exports + Overnights + Confidence + ATM	0.679	***	0.637	***	0.653	***	**0.557**	***	0.439	***
AR-U-MIDAS										
Overnights + Confidence	0.823		0.814		0.922		0.754	*	0.810	
ATM + Confidence	0.715	*	0.666	*	0.662	***	0.588	***	0.588	***
BoP exports + Confidence	0.655	**	0.668	**	0.631	***	0.495	***	0.407	***
BoP exports + Overnights	0.880		0.849		0.658	***	**0.425**	***	0.407	***
BoP exports + Overnights + Confidence	0.679	**	0.676	**	0.629	***	0.518	***	0.407	***
BoP exports + Confidence + ATM	**0.641**	***	**0.617**	***	**0.589**	***	0.467	***	**0.397**	***
BoP exports + Overnights + Confidence + ATM	0.688	**	0.656	**	0.599	***	0.503	***	0.405	***
AR-M-MIDAS										
Overnights + Confidence	0.634	**	0.619	**	0.582	***	0.577	***	0.582	***
ATM + Confidence	**0.595**	***	**0.577**	**	0.544	***	0.509	***	0.509	***
BoP exports + Confidence	0.633	**	0.620	**	0.615	**	0.593	***	0.355	***
BoP exports + Overnights	1.088		1.022		0.647	***	0.492	***	**0.329**	***
BoP exports + Overnights + Confidence	0.632	***	0.609	***	0.550	***	0.503	***	0.338	***
BoP exports + Confidence + ATM	0.632	***	0.611	***	0.538	***	0.484	***	0.359	***
BoP exports + Overnights + Confidence + ATM	0.659	***	0.641	***	**0.524**	***	**0.465**	***	0.358	***

TABLE 1. Relative RMSE performance of nowcast pooling against an AR benchmark

Notes: See Section 4 for a detailed description of the variables and the information used for each nowcast. Ratios of the RMSE with respect to an AR model. A ratio lower than 1 denotes a forecasting gain by the bridge and/or MIDAS models. $*$, $**$ and $***$ indicate the forecasts which are statistically superior to the ones from the benchmark at a confidence level of 10, 5 and 1 per cent, respectively, according to the Diebold and Mariano (1995) test modified for short samples by Harvey *et al.* (1997). The numbers in bold denote the minimum relative RMSE within each model and in each period. The numbers dark-shaded and with white font denote the minimum relative RMSE for each evaluation period across all models and combinations of indicators. The light-shaded areas represent the cases where the MIDAS model is statistically superior to the respective bridge equation (at least at a 10 per cent significance level).

three evaluation periods, it is possible to obtain a projection that is statistically superior to the univariate benchmark in 96.4 per cent of the cases.

Focusing on the best combinations within each model in each period (the bold numbers in the table), they all provide results that are statistically superior to the AR benchmark. The good performances are shared by different combinations but a common feature emerges across all models: the consumer confidence indicator is always part of the best performing combination in the first two periods and BoP exports are always included in the best combination in the last three projection moments.

The overall minimum relative RMSE for each evaluation period across all models and combinations of indicators (the numbers dark-shaded with white font in the table) is always produced by a MIDAS model: the AR-M-MIDAS in four cases and the AR-U-MIDAS in one case. Not only the best performing MIDAS specification changes over time, but the best combination of predictors also changes for the different within-quarter information sets of the variables. The AR-M-MIDAS model works particularly well in the three months of the reference quarter: it delivers the best results in first two months of the reference quarter by combining ATM/POS transactions and consumer confidence and, in the last month of the quarter, by combining the four individual indicators. In the last two evaluation periods, when more data is already observed for the reference quarter, the preferred combination is BoP exports and overnight stays, first obtained from the AR-U-MIDAS model and, then, from the AR-M-MIDAS model in the last period.

Another way to compare the alternative mixed-frequency models is to compute the RMSE of the different MIDAS models relative to the RMSE of the bridge equations for each combination of indicators. The light-shaded areas in Table 1 represent the cases where the forecasts from a MIDAS model are statistically superior to the respective forecasts from the bridge equation, at least at a 10 per cent significance level.

The most useful forecast combinations of MIDAS models should outperform both the AR benchmark and the competing bridge equation (Schumacher 2016). In Table 1 , these are cases where the ∗s are light-shaded. The statistically significant improvements of MIDAS models relative to both benchmarks simultaneously occur, in particular, in the first two periods: in around 35 per cent of the cases for AR-U-MIDAS and in more than 70 per cent of the cases for both AR-MIDAS and AR-M-MIDAS. Considering the five evaluation periods and the best seven combinations of indicators, AR-M-MIDAS is the model with best overall performance: it delivers projections that are statistically better that both benchmarks in around 57 per cent of the cases. Overall, and taking into account all evaluation periods, nowcast combinations that comprise 3 and 4 indicators tend to be more reliable, in the sense that they tend to outperform both benchmarks more frequently than combinations with less indicators.

Final remarks

Tourism exports are an extremely important component of Portuguese international trade of goods and services. Short-run forecasts of this variable play a relevant role in the monitoring of Portuguese economic activity and external accounts.

The purpose of this article is to nowcast the real growth of quarterly tourism exports using four different monthly indicators in a recursive pseudo real-time exercise. We resort to two single-equation approaches that deal with mixed-frequency data: bridge equations and MIDAS regressions. Bridge equations are one of the most used techniques to link monthly and quarterly variables. In these models, the variables on both sides of the equation are on the same (low) frequency: in our case, monthly indicators are aggregated to their corresponding quarterly values. In contrast, in MIDAS regressions, the observations of the low-frequency dependent variable are linked directly to high-frequency observations of the predictors without any previous temporal aggregation. Different specifications of bridge and MIDAS models with single indicators and combination of nowcasts are evaluated in this article.

The results obtained suggest that, as expected, using mixed-frequency models with short-term indicators contributes to increase nowcast accuracy in comparison to a univariate benchmark. In general, MIDAS models tend to fare better than traditional bridge models for the majority of the predictors and evaluation periods, but the differences are higher when less current-quarter information is available. Nowcast combinations of both bridge and MIDAS regressions always provide gains over single-indicator models. In fact, a general finding common to all mixed-frequency models considered is that the AR benchmark can always be outperformed by the best performing combination of nowcasts in every evaluation period and that the differences in terms of relative RMSE are statistically significant. Overall, the best performing nowcast is always obtained from a combination of projections of a MIDAS variant with AR dynamics, which suggests the use of this class of mixed-frequency models for short-term forecasting tourism exports.

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Appendix: Detailed results of nowcast pooling for all models considered

	1st m Qt	2nd m Qt	3rd m Qt	1st m Qt+1	2nd m Qt+1
Bridge models					
Overnights + ATM	1.144	1.056	0.731***	0.679***	0.679***
Overnights + Confidence	0.861	0.845	0.755*	0.769*	0.786
ATM + Confidence	0.754*	0.727	0.623***	0.599***	0.599***
BoP exports + Confidence	0.745*	0.691**	0.694**	0.493***	0.450***
BoP exports + Overnights	1.046	0.981	0.672***	0.464***	0.376***
BoP exports + ATM	1.103	0.984	0.619***	0.481***	0.421***
Overnights + Confidence + ATM	0.822	0.801*	0.652***	0.624***	0.627***
BoP exports + Overnights + Confidence	0.805*	0.762**	0.633**	0.473***	0.406***
BoP exports + Confidence + ATM	0.794*	0.747**	0.592***	0.483***	0.435***
BoP exports + Overnights + ATM	1.094	0.995	0.638***	0.492***	0.417***
BoP exports + Overnights + Confidence + ATM	0.848*	0.802**	0.604***	0.488***	0.427***
AR-MIDAS					
Overnights + ATM	1.196	1.186	1.127	0.813***	0.758**
Overnights + Confidence	0.611**	0.599**	0.656**	0.655**	0.738*
ATM + Confidence	0.609**	0.604**	0.657**	0.614**	0.614**
BoP exports + Confidence	0.683**	0.631**	0.662**	0.662**	0.433***
BoP exports + Overnights	0.995	0.822**	0.770**	0.574***	0.388***
BoP exports + ATM	1.022	0.857**	0.807**	0.561***	0.421***
Overnights + Confidence + ATM	0.624***	0.623***	0.689***	0.642***	0.649**
BoP exports + Overnights + Confidence	0.668**	0.613***	0.624***	0.569***	0.422***
BoP exports + Confidence + ATM	0.657**	0.624***	0.637***	0.561***	0.434***
BoP exports + Overnights + ATM	1.033	0.881**	0.830**	0.583***	0.426***
BoP exports + Overnights + Confidence + ATM	0.679***	0.637***	0.653***	0.557***	0.439***
AR-U-MIDAS					
Overnights + ATM	1.313	1.195	0.910	0.800**	0.728***
Overnights + Confidence	0.823	0.814	0.922	0.754*	0.810
ATM + Confidence	0.715*	0.666*	0.662***	0.588***	0.588***
BoP exports + Confidence	0.655**	0.668**	0.631***	0.495***	0.407***
BoP exports + Overnights	0.880	0.849	0.658***	0.425***	0.407***
BoP exports + ATM	0.846*	0.815**	0.673***	0.511***	0.415***
Overnights + Confidence + ATM	0.794	0.751*	0.712**	0.628***	0.613***
BoP exports + Overnights + Confidence	0.679**	0.676**	0.629***	0.518***	0.407***
BoP exports + Confidence + ATM	0.641***	0.617***	0.589***	0.467***	0.397***
BoP exports + Overnights + ATM	0.899	0.835*	0.658***	0.553***	0.417***
BoP exports + Overnights + Confidence + ATM	0.688**	0.656**	0.599***	0.503***	0.405***
AR-M-MIDAS					
Overnights + ATM	1.154	1.226	0.945	0.662***	0.668***
Overnights + Confidence	0.634**	0.619**	0.582***	0.577***	0.582***
ATM + Confidence	0.595***	0.577**	0.544***	0.509***	0.509***
BoP exports + Confidence	0.633**	0.620**	0.615**	0.593***	0.355***
BoP exports + Overnights	1.088	1.022	0.647***	0.492***	0.329***
BoP exports + ATM	0.978	0.981	0.649***	0.489***	0.359***
Overnights + Confidence + ATM	0.620***	0.613***	0.545***	0.516***	0.520***
BoP exports + Overnights + Confidence	0.632***	0.609***	0.550***	0.503***	0.338***
BoP exports + Confidence + ATM	0.632***	0.611***	0.538***	0.484***	0.359***
BoP exports + Overnights + ATM	1.044	1.035	0.647***	0.483***	0.363***
BoP exports + Overnights + Confidence + ATM	0.659***	0.641***	0.524***	0.465***	0.358***

TABLE A.1. Relative RMSE of nowcast pooling against the AR benchmark

Notes: See Section 4 for a detailed description of the variables and information used for each nowcast. Ratios of the RMSE with respect to an AR model. A ratio lower than 1 denotes a forecasting gain by the bridge and/or MIDAS models. $*$, $**$ and $***$ indicate the forecasts which are significantly more accurate than the benchmark at a confidence level of 10, 5 and 1 per cent, respectively, according to the Diebold and Mariano (1995) test modified for short samples by Harvey *et al.* (1997).

	1st m Qt	2nd m Qt	3rd m Qt	1st m Qt+1	2nd m Qt+1
AR-MIDAS					
Overnights + ATM	1.045	1.123	1.542	1.197	1.116
Overnights + Confidence	0.709***	0.708***	0.869	0.852*	0.938
ATM + Confidence	0.808***	0.830**	1.056	1.026	1.026
BoP exports + Confidence	0.917	0.912	0.954	1.343	0.964
BoP exports + Overnights	0.951	0.837	1.146	1.237	1.032
BoP exports + ATM	0.927	0.871	1.304	1.165	0.999
Overnights + Confidence + ATM	0.760***	0.778***	1.057	1.029	1.035
BoP exports + Overnights + Confidence	0.829**	0.804**	0.986	1.203	1.041
BoP exports + Confidence + ATM	0.828**	0.835*	1.076	1.162	0.999
BoP exports + Overnights + ATM	0.945	0.886	1.301	1.185	1.020
BoP exports + Overnights + Confidence + ATM	0.801**	0.794**	1.081	1.141	1.029
AR-U-MIDAS					
Overnights + ATM	1.147	1.132	1.245	1.179	1.072
Overnights + Confidence	0.956	0.963	1.222	0.980	1.030
ATM + Confidence	0.948	0.916	1.064	0.982	0.982
BoP exports + Confidence	0.879	0.967	0.909	1.004	0.905*
BoP exports + Overnights	0.841	0.865	0.979	0.916	1.084
BoP exports + ATM	0.767*	0.829	1.088	1.061	0.987
Overnights + Confidence + ATM	0.966	0.938	1.091	1.006	0.978
BoP exports + Overnights + Confidence	0.843*	0.887	0.992	1.095	1.002
BoP exports + Confidence + ATM	0.807**	0.827*	0.995	0.966	0.912
BoP exports + Overnights + ATM	0.822*	0.839	1.031	1.125	1.000
BoP exports + Overnights + Confidence + ATM	0.812**	0.819*	0.992	1.031	0.948
AR-M-MIDAS					
Overnights + ATM	1.008	1.161	1.294	0.974	0.984
Overnights + Confidence	0.736***	0.733***	0.771***	0.750**	0.740
ATM + Confidence	0.789***	0.793***	0.874	0.850**	0.850**
BoP exports + Confidence	0.850**	0.897	0.887	1.202	0.788***
BoP exports + Overnights	1.040	1.042	0.963	1.060	0.876
BoP exports + ATM	0.887	0.998	1.049	1.016	0.853**
Overnights + Confidence + ATM	0.754***	0.765***	0.836*	0.827**	0.829**
BoP exports + Overnights + Confidence	0.785***	0.800***	0.868*	1.062	0.833**
BoP exports + Confidence + ATM	0.797***	0.819***	0.908	1.003	0.827***
BoP exports + Overnights + ATM	0.955	1.040	1.014	0.982	0.870
BoP exports + Overnights + Confidence + ATM	0.777***	0.800***	0.867	0.953	0.838**

TABLE A.2. Relative RMSE of nowcast pooling against bridge models

Notes: See Section 4 for a detailed description of the variables and the information used for each nowcast. Ratios of the RMSE with respect to bridge models. A ratio lower than 1 denotes a forecasting gain by the MIDAS models. $*$, $**$ and $***$ indicate the forecasts which are significantly more accurate than the benchmark at a confidence level of 10, 5 and 1 per cent, respectively, according to the Diebold and Mariano (1995) test modified for short samples by Harvey *et al.* (1997).