The Impact of Quantitative Easing on Bank Lending in the UK

Evidence from an Agent-Based Model

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Abstract

Expanding bank lending by increasing the liquidity throughout the banking system is one of the core objectives of the asset purchase program (APP) launched by the Bank of England in 2009. Yet, the data of Office for National Statistics shows an obvious fall in total bank lending despite of the noticeable increase in households borrowing from banks after the introduction of the program. This paper attempts to explain the drop in bank lending using an agent-based computational economics (ACE) approach. The baseline model contains four types of agents – households (HHs), big firms (BFs), small and medium enterprises (SMEs), and banks - interacting monthly for a period of 50 months in an environment that simulates bank lending markets in the UK after APP was introduced in 2009. The ACE is anchored to the actual values of several variables - such as homeownership statistics and nonfinancial firms leverage ratio - around the time of the program initiation. Similar to the actual data, simulation results indicate that the rise in the amount of mortgages was not enough to counter the significant decrease in business loans which represents the main cause of the shrinkage in total bank lending. A combination of lower bond yields and Basel III capital adequacy requirements on banks has been found to play a role in the drop in the amount of bank loans to businesses. Banks respond to the riskier asset pools, resulted from the tendency of the BFs to replace bank financing with lower cost security debt, by expanding mortgages and decreasing the amount of loans granted to SMEs.
1. Introduction

The financial crisis of mid 2007 produced severe recessions in major economies and raised the threat of a total collapse of the global financial system. The crisis clearly affected the UK economy which witnessed obvious drop in retail sales and rise in unemployment (Figure 1), and the economy officially approached a recession period in 2008 Q4 when the GDP fell by about 1.5% as Figure 2 shows.

Figure 1: UK Unemployment Rate (%; Seasonally Adjusted)

![UK Unemployment Rate Graph](http://www.ons.gov.uk/ons/datasets-and-tables/index.html)

Source: ONS (http://www.ons.gov.uk/ons/datasets-and-tables/index.html)

Figure 2: Gross Domestic Product (£ Million; Seasonally Adjusted)

![GDP Graph](http://www.ons.gov.uk/ons/datasets-and-tables/index.html)

Source: ONS (http://www.ons.gov.uk/ons/datasets-and-tables/index.html)
Similar to the monetary authorities of the other countries, the Bank of England (BoE hereafter) reduced its short-term policy rate to exceptionally low levels. The Monetary Policy Committee (MPC hereafter) of the Bank decreased many times the policy rate which reached 0.5% -effectively its lower bound- early in 2009. Nevertheless, the substantial monetary loosening proved not to be sufficient to support aggregate demand and hence to help economy to recover. Consequently, in order to inject more liquidity into the economy and boost aggregate expenditure, MPC launched in March 2009 an open-ended asset purchase program (APP hereafter) to buy longer term securities. The program started with £75 billion of asset purchases then expanded in several occasions up to £375 billion in July 2012. Figure 3 presents the key moments of APP between March 2009 and July 2012.

**Figure 3: Bank of England’s Asset Purchase Program (APP) Timeline**

<table>
<thead>
<tr>
<th>Date</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-Mar-2009</td>
<td>Bank of England Announces £75 Billion Asset Purchase Programme</td>
</tr>
<tr>
<td>7-May-2009</td>
<td>MPC Increases the Size of Asset Purchase Programme by £50 Billion to £125 Billion</td>
</tr>
<tr>
<td>6-Aug-2009</td>
<td>MPC Increases the Size of Asset Purchase Programme by £50 Billion to £175 Billion</td>
</tr>
<tr>
<td>5-Nov-2009</td>
<td>MPC Increases the Size of Asset Purchase Programme by £25 Billion to £200 Billion</td>
</tr>
<tr>
<td>6-Oct-2011</td>
<td>MPC Increases the Size of Asset Purchase Programme by £75 Billion to £275 Billion</td>
</tr>
<tr>
<td>9-Feb-2012</td>
<td>MPC Increases the Size of Asset Purchase Programme by £50 Billion to £325 Billion</td>
</tr>
<tr>
<td>5-Jul-2012</td>
<td>MPC Increases the Size of Asset Purchase Programme by £50 Billion to £375 Billion</td>
</tr>
</tbody>
</table>

Source: Bank of England (http://www.bankofengland.co.uk)

According to Joyce, Tong, and Woods (2011) the influence of quantitative easing (QE) policy measures may be conveyed into the real economy through five transmission channels including policy signaling, portfolio rebalancing, liquidity, broad money, and confidence. As Figure 4 illustrates, while the effects of QE spread directly into the wider economy through confidence impact on aggregate expenditure, asset prices and returns represent the path of transmission for the other four channels except broad money channel which utilizes also bank lending path. For instance, when a central bank buys debt securities from outside the banking system, it produces new electronic money which it deposits into reserve account of
the seller’s bank which, in turn, credits the same amount into the seller’s account. This increases liquidity within the banking system and may induce banks to expand their lending to households and businesses. Nonetheless, Office for National Statistics (ONS) data shows that bank lending in the UK fell by about £421.4 billion in four years after APP was introduced early in 2009.

**Figure 4: The Transmission Channels of Quantitative Easing (QE)**

![Diagram showing the transmission channels of Quantitative Easing](image)

The sectoral balance sheets and financial accounts available from ONS indicate that banks in the UK provide loans primarily to households (mostly in the form of mortgages) and nonfinancial businesses, and Figure 5 presents the amounts of bank lending to the two sectors between 1997 and 2012. As the Figure demonstrates, bank lending to households and nonfinancial businesses witnessed a period of stable growth before the financial crisis. However, while households borrowing continued to grow after 2008, nonfinancial firms borrowing showed steady fall in the same period. Accordingly, the shrinkage in the amount of loans to nonfinancial businesses has been the main cause of the decrease in total bank lending mentioned above.

Nonfinancial businesses can be categorized, in terms of size, into two groups: big firms (BFs) and small and medium enterprises (SMEs). The distinction is important in the context of this paper because the accessibility to debt financing is different between the two types. BFs have good access to several debt
finances, whereas borrowing from banks represents the sole source of debt financing for SMEs. As Figure 6 indicates, the monthly amounts outstanding of UK bank loans to both BFs and SMEs according to BoE dataset have shown clear drop especially after November 2011.¹

**Figure 5: Bank Lending to Households and Non-Financial Corporations (£Million)**

![Graph showing bank lending to households and non-financial corporations](http://example.com/bank-lending-chart)


**Figure 6: Bank Lending to Big Firms and Small and Medium Enterprises (£Million)**²

![Graph showing bank lending to big firms and SMEs](http://example.com/bank-lending-chart2)

Source: Bank of England Interactive Database ([http://www.bankofengland.co.uk/boeapps/iahd/newintermed.asp](http://www.bankofengland.co.uk/boeapps/iahd/newintermed.asp))

¹ According to BoE dataset, BFs and SMEs bank borrowing fell by 12.25% and 13.49% respectively between April 2011 and November 2013.

² The charts are prepared using the data on sterling monthly amounts outstanding of banks loans to SMEs and to all nonfinancial businesses from BoE’s Statistical Interactive Database.
Accordingly, to properly clarify the fall in bank lending, it is important to examine the drivers of the shrinkage in the size of business loans especially the interaction between different credit markets taking into account the impact of BoE’s APP on the relative costs of alternative debt instruments. Utilizing a macro agent-based computational economics (ACE here after) methodology, this paper tries to build a sound explanation of the developments in the UK debt markets since APP was introduced. The ACE model of the paper follows the data driven approach recommended by Markose (2013) in the sense that the distributional assumptions about the financial characteristics of different economic sectors such as households, nonfinancial businesses and banks are based on empirical foundations.

The study of the economy by means of ACE and network analysis is a relatively new field (dates back to the 90s). It also represents a suitable approach to respond to the criticisms raised on the methodological foundations of the macroeconomic theory. Because of their failure in predicting the great recession of 2008-09 and evaluating the consequences of such a recession, macro models and their usage in policy analysis have received severe criticism (Wieland, V. (2010)). Macroeconomists were accused of heavy dependence on dynamic stochastic general equilibrium (DSGE) models that are built around special cases where market inefficiencies are not possible (Stiglitz (2011)) and institutional details and financial interconnections in the provision of liquidity, capital adequacy and solvency are ignored (Markose (2013)). Buiter (2009) points out that “... the typical graduate macroeconomics and monetary economics training received at Anglo-American universities during the past 30 years or so, may have set back by decades serious investigations of aggregate economic behaviour and economic policy-relevant understanding”. This view is supported by Nobel Prize Winner Paul Krugman -in the Economist, June 2010- who indicates that “most work in macro-economics in the past 30 years has been useless at best and harmful at worst”. In particular, critics of the standard macro models have used the aggregation of individual economic units, the perfect rationality of these units, and the assumption of equilibrium as a ground to attack these models (Lengnick (2011)). First, the majority of macro models link the macro movements directly to the individual units’ behaviours -either through equating the aggregates to the representative units or by adding up the
individual decisions to find the aggregates- to provide a proper microfoundation. However, several experiments have indicated that the aggregate behaviour of big groups usually differs considerably from the behaviours of the individual units. For instance Schelling’s (1969) analysis of racial segregation models points out that interaction between individuals may create significant segregation in big cities even if individual preferences for residing in areas dominated by people of the same race are slight. More recently in the context of the 2007 financial crisis, many have noted the pitfall of the macroeconomic models where extrapolation of the behaviour of the representative optimizing agents can result in fallacy of composition. Specifically, with microprudential policies where the risk is specified at the level of individual units and the implications of their interaction with each other are ignored, systemic-wide risks and instabilities are not modelled or managed (For example, Markose (2013) and Goodhart et al (2009)). Moreover, the assumption of perfect rational utility-maximizing agent has proven to be very unrealistic. Rather than complex utility optimization approach which requires everyone to have perfect information, individuals tend to use relatively simple behavioural rules to make decisions (Akerlof (2002)). Lastly, most of macro models are built around the assumption of a stable state once reached there will be no incentive for any further changes (i.e. equilibrium), and if the economy for some reason deviates for that state, it return to it through quick adjustment processes. Yet, it has been frequently proven that such adjustment processes barely exist (Gaffeo et al. (2008), Kirman (2006), Ackerman (2002)) and that real markets are often characterized by multiple equilibria, volatility, and coordination problems (Arthur (2006)).

Generally, existing macro ACE models can be classified into three main categories (Chan and Steiglitz (2008)). The models in the first category combine conventional economic theory with computational techniques. For instance, Arifovic (1994), specifies that rational expectations equilibrium can be attained if the agents employ genetic algorithm to make production decision. Additionally, Chen (2003) indicates that overlapping generations (OLG) models -in which agents use learning algorithms to maximize utility- are employed in several studies about inflation and price stability. The second category of ACE models consists of massive real economy models. Models such as EURACE and ASPEN projects which try to mimic the entire
EU and US economies respectively, include substantial simulations of the agent in real world economies (Chan and Steiglitz (2008)). In contrast, the third group of ACE models - to which the model of this paper belongs - contain a basic picture of the real economy and attempt to explain macroeconomic developments by simulating the agents in the basic economies they address. For instance, Steiglitz et al. (1996) introduce a gold-food economy with zero-intelligence agents.³ Their results point out that existence of arbitrage opportunities is enough to stabilize market prices in the long run. Bruun (2008) implements an agent-based Keynesian model and confirms Keynes argument that the self-organizing properties of an economy can operate without depending on price changes as an equilibrating factor. Using a simple baseline model, Lengnick (2011) indicates that simulation results are able to imitate several empirical facts like the presence of reasonable levels of involuntary unemployment, empirical laws like Philips curve, the dynamic correlation between inflation and output, and money neutrality.

The remaining of the paper is structured as follows. Section 2 outlines the ACE model and provides a full description of the model agents and their behaviours. Simulation outcomes are presented in details in section 3, then the last section contains concluding remarks of the paper.

2. The Model

The model of this paper contains four types of agents: 1,000 households (HHs), 25 big firms (BFs), 210 small and medium enterprises (SMEs) and 10 banks which interact monthly for a period of 50 months in an environment that simulates bank lending markets in the UK after APP was introduced in 2009. While the number of households with at least one adult working in 2009 was 21.464730 million⁴, there were 4.923320 million businesses 99.9% (i.e. 4.918915 million) of which were SMEs.⁵ This indicates a proportion of 0.229

³ Agents in this model have to obtain an essential good (food) either by producing it or by purchasing it using another good (gold) that can be produced.
⁴ In 2009, there were 25.83 million households 16.9% of them were workless (i.e. with no adult working). Yet the model assumes that only non-workless households would be interested in obtaining mortgages to buy houses.
⁵ Small and Medium Enterprise Statistics for the UK and Regions; Enterprise Directorate; The Department for Business, Innovation and Skills (BIS); Available at: http://webarchive.nationalarchives.gov.uk/20110920151722/http://stats.bis.gov.uk/ed/sme/index.htm
between the number of SMEs and the number of HHs. Hence, if HHs population size in the model is set to 1,000, the number of SMEs would be 229. Moreover, the number of BF is set to 25 to account for the very Big firms that are not captured by the distribution of BF's total assets described later. Lastly, each of the HHs, BF, and SMEs would choose only one preferred bank to do business with. This implicates that the assets and liabilities in the balance sheet of any bank are the horizontal sums of the corresponding assets and liabilities in the balance sheets of the agents who choose to deal with this bank. For example, the amount of deposits on the liabilities side of a bank balance sheet is the sum of the cash holdings of all HHs, BF, and SMEs who favour this bank. Hence, the choice of the number of banks will not affect the model.

Each household earns an income and accumulates its wealth at each period only in the form of housing and cash (deposited with the preferred bank). To expand housing wealth, a household needs to have cash that is sufficient to cover the down payment (the deposit) and to obtain a mortgage from the bank it does business with (the preferred bank). Productive sector firms (BFs firms and SMEs) employ physical capital and cash to operate and finance their operations using a mixture of debt financing and equity. The amount of physical capital (and total assets) defines the a firm’s size which, in turn, determines its accessibility to different debt markets; that is, while SMEs are restricted to bank borrowing, BF can also issue debt securities to raise debt financing. Banks hold cash (accept deposits) of HHs, BF, and SMEs, and provide loans in the form of mortgages to households and business loans to BF and SMEs. The differences in debt markets accessibility for HHs, BF, and SMEs reflect on the market power of banks, they enjoy relatively stronger market position in mortgages and loans to SMEs markets rather than loans to BF market. The following sections provide a further description of the starting conditions and the agents and explain the behaviour of these agents over the simulation period.

Before describing the model agents and their behaviours, the following section presents some facts about the UK economy around the launch of APP in 2009. These facts represents the empirical base to which the model is anchored.
2.1 Empirical Details on the UK Economy

This section surveys the empirical facts about the nonfinancial sectors (including households and nonfinancial businesses) and banks in the UK around the time of APP introduction. It aims to provide an empirical foundation for the model.

2.1.1 Housing and Mortgages Markets

As Figure 7 illustrates, after having a long period of persistent growth between 1996 and 2007, UK house prices witnessed a noticeable drop in the years following the financial crisis. In particular, the average house price in the UK, according to Nationwide’s dataset\(^6\), increased by about 258% in 12 years from £51,367 in 1996 Q1 to £183,959 in 2007 Q4, then fell by more than 18.6% down to £149,709 in 2009 Q1. Moreover, ONS home ownership and renting data\(^7\) indicates that 64% of homes in the UK were owner-occupied (the remaining 36% of homes were rented), and that about 52% of the home owners have mortgage obligations.

Figure 7: Average House Price in the UK (1996-2014)

\(^6\) [http://www.nationwide.co.uk/about/house-price-index/download-data#xtab:uk-series](http://www.nationwide.co.uk/about/house-price-index/download-data#xtab:uk-series).

Figure 8: Quarterly Amounts Outstanding of Mortgages in the UK (1996-2014)

Source: Quarterly amounts outstanding of monetary financial institutions’ sterling net secured lending to individuals and housing associations (in sterling millions) seasonally adjusted available at the Bank of England’s Statistical Interactive Database (http://www.bankofengland.co.uk/boeapps/iadb/NewInterMed.asp?Travel=NixSSx)

Figure 9: Quarterly Average Household Mortgage Indebtedness in the UK (1996-2014)


Figure 8 demonstrates that the mortgages market has showed a significant expansion in volume during the past two decades. More specifically, the gross amount outstanding of mortgages has continuously grown from £366.764 billion in 1996 Q1 to about £1.111 trillion in 2014 Q4 with an exception of the second
half of 2008 where it fell by 7.1%. Likewise, the average household mortgage indebtedness (Figure 9) displayed a clear increase until 2009 Q1 where is fell by more than £1,000 from £50,150 to £49,070. However, while the fall in gross mortgages was temporary and lasted for a short period of time, average household mortgage debt needed more than four years to start recovering properly from its post crisis drop. Indeed, average household mortgage debt fell by about 5.1% between 2008 Q4 and 2012 Q1 then started to increase again.

2.1.2 Households Income Distribution

As shown in Figure 10, the household income in the UK follows a lognormal distribution. According to Institute for Fiscal Studies (IFS)\(^8\), the average weekly income of a household in 2008-09 financial year was £560.64 (an equivalent of £2,429.43 per month\(^9\)) with 50% of the households making £450.52 or less a week (or £1,951.84 a month).

Figure 10: The Probability Distribution of Household Weekly Income (2008-09)

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\(^9\) Monthly income = Weekly Income x 52 (weeks a year) / 12 (months a year).
2.1.3 Nonfinancial Businesses Financing Structure

During the past two decades, the share of debt financing in the balance sheets of nonfinancial has shown a stable trend. Particularly, after a relatively long period of rather small fluctuations around some level, the leverage ratio of the nonfinancial rapidly rise to some peak after which it falls a bit to become stable around some higher level compared to the previous stability period. For instance, the leverage ratio in Figure 11 was stable around its mid-30% level for five years between 1997 Q1 and 2001 Q4, then increased quickly to reach about 45% by 2002 Q4. Half a year later, the ratio fell and stayed stable around 40% for more than four years. In 2009 Q1, the leverage ratio was 51.66%\(^\text{10}\) which represents its highest level in a few decades.

**Figure 11: Nonfinancial Firms Leverage Ratio**

The composition of nonfinancial firms’ debt financing has changed towards more security debt and less bank lending since 1997 especially after the launch of APP in 2009 Q1 as Figure 12 reveals. More precisely, nonfinancial firms increased the share of security debt in their debt mix from about 30.5% at the beginning

\(^{10}\) Calculated by dividing the total debt of nonfinancial firms (£1,709,646 million) on their total liabilities (£3,309,550 million) in 2009 Q1.
of 1997 to 43.3% in the first quarter of 2004. However, this share witnessed a continuous fall until 2009 Q1 (about 32.7%\textsuperscript{11}) where it started to increase clearly.

Figure 12: The Shares of Bonds and Bank Loans in Nonfinancial Firms Total Debt

Lastly, the financial balance sheets data of nonfinancial corporation sector issued by ONS indicates that cash holdings of nonfinancial businesses in 2009 Q1 represented about 12.83% of their total assets.\textsuperscript{12}

2.1.4 Funding for Lending Scheme

In July 2012, BoE and HM treasure introduced the Funding for Lending Scheme (FLS) to motivate banks to increase their lending to real economy through providing medium-term finances whose value and price rely on the lending performance of the borrowing bank (Churm et al. (2014)). Additionally, the FLS was extended in April 2013 to allow banks to borrow from the scheme until January 2015 and to provide some incentives to expand lending to SMEs. Baddeley-Chappell (2013) indicates that FLS has had a substantial impact on the mortgage market through lowering mortgage rates, which are down by about 1%. He believes that “this reduction has been achieved not through the use of the scheme, but rather through the

\textsuperscript{11} This is equal to the ratio of nonfinancial corporation security debt in 2009 Q1 (£333,907 million) to the sum of total security debt and total bank lending in the same quarter (£1,021,517 million).

\textsuperscript{12} Calculated by dividing the total amount of cash and deposits of the nonfinancial firms (£424,763 million) on their total liabilities (£3,309,550 million) in 2009 Q1.
potential funding capacity that the scheme introduced. This has reduced demand for, and hence the price of, other funding routes (such as consumer savings)”. Moreover, Al-Eyd and Berkmen (2013) point out that in spite of the lower funding cost, aggregate bank lending to the private sector has not expanded. They specify several factors that might have limited the influence of FLS including the absence of big cost advantages, the weak demand for credit, the financial health of the UK banks, and the design of capital charges on FLS financing.

2.2 Agents Description and Initial Conditions

As mentioned earlier, the four types of agents (HHs, BFs, SMEs, and banks) have linkages in several credit markets including mortgages market and business loans markets. The presence and the size of a linkage between two agents of two types (similar to these in Figure 7) in a given period relies on the initial (financial) circumstances of the two agents at the beginning of the period and their behaviours during that period. The initial financial positions of the different types of agents (Figure 8) at the start of the simulation period were estimated using the actual data from ONS, Nationwide, and The Money Charity around the launch of APP in March 2009.

Figure 7: Network Representation of the Model
2.2.1 Households

As Figure 8 shows, each household finances its holding of housing and cash using a mixture of its own resources and mortgages obtained from the preferred bank it does business with. The model assumes that all the properties (houses) are identical and traded at the same price of £149,400\textsuperscript{13} and that HHs deposit all their cash holdings with banks. As mentioned earlier, only 64% of UK households own at least one property according to ONS data. To calibrate this fact, the model introduces a random number of houses variable (whose probability distribution is shown in Figure 9) which multiplied by average house price to obtain the initial housing wealth for each household. The initial amount of cash held by HHs is assumed to be uniformly distributed between £5,000 and £50,000. Moreover, since that only 52% of the home owners have mortgages with an average mortgage debt of £49,070 (in 2009 Q1), the model assumes that the

\textsuperscript{13} Although the average house price in the UK in 2009 Q1 was £149,709 according to Nationwide data, the model sets house price to £149,400 to avoid fractions when calculating mortgage payments.
amount of mortgage liability of HHs at period 1 is uniformly distributed between £0 and £70,965\textsuperscript{14}. A household’s equity (net worth) is the difference between total assets and mortgage liability of the household. Lastly, basing on the actual income distribution Households below average income (HBAI) shown before, HHs initial income in the model follows a lognormal distribution which is estimated using the monthly equivalents of IFS’s parameters of the weekly income distribution (in 2009 Q1).\textsuperscript{15}

### Figure 9: The Probability Distribution of the Number of Houses per Household in Period 1

<table>
<thead>
<tr>
<th>Number of Houses</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability</td>
<td>0.36</td>
<td>0.16</td>
<td>0.16</td>
<td>0.16</td>
<td>0.16</td>
</tr>
</tbody>
</table>

#### 2.2.2 Firms (BFs and SMEs)

BFs and SMEs in the model use physical assets and cash to run their operations. The model assumes that the physical capital of BFs is uniformly distributed between £5 million and £300 million to differentiate BFs from SMEs whose physical capital follows a uniform distribution between £50,000 and £1 million. Since, as mentioned before, the ratio of nonfinancial businesses liquid assets holdings to their total financial liabilities in 2009 Q1 was 0.1283, the amount of cash held by each firm in period 1 (the beginning of simulation) represents 12.83% of the total assets of that firm.

Both BFs and SMEs finance their assets by a mixture of equity and debt financing. However, there are two main differences between the two firm types on the liabilities side of the balance sheet. First, because of their stronger financial positions, BFs enjoy more flexibility in debt markets where they can obtain bank loans or issue debt securities to the public to raise debt finances. In addition, the strong financial position enables BFs not only to build flexible debt structure, but also to have higher leverage in their balance sheets. Consequently, while the leverage (debt to total liabilities or assets) ratio of BFs in period 1 is set

\textsuperscript{14}This is half the amount of a new mortgage which is equal to (1 – down payment or deposit ratio or 0.05) x average house price. The uniform distribution is used here because of the lack of data on the actual mortgages distribution. The upper limit of the distribution is set relatively not very far from the average mortgage indebtedness to account for the big mass at zero (48% of HHs have no mortgages).

\textsuperscript{15}Data is available at: [http://www.ifs.org.uk/tools_and_resources/incomes_in_uk](http://www.ifs.org.uk/tools_and_resources/incomes_in_uk).
51.66% (the leverage ratio of nonfinancial businesses in 2009 Q1), SMEs finance only 40% of their total assets by borrowing from banks. Finally, since the security debt of nonfinancial corporations in 2009 Q1 represented 32.7% of their total debt, the model assumes that the balances of bank loans and bonds in the initial balance sheet of each big firm represent 31.87% and 19.79% respectively the firm’s total assets.

2.2.3 Banks

Banks represent the heart of the model since they have with all other agents in the model. Each non-bank agent selects randomly a preferred bank to deposit cash and to obtain debt financing. Thus, the balances of debt assets (mortgages and loans) and liabilities (deposits) of a bank is the horizontal sum of the corresponding liabilities and assets of the non-bank agents who prefer to do business with that bank. Banks in this model are allowed to obtain costless liquidity (through the funding for lending scheme and/or by using the substantial amounts of excess reserves they keep with the BoE) to provide virtually unlimited amount of credit; however, they have to adhere to capital adequacy requirements, in particular to attain equity (or core or tier 1 capital) to risk weighted assets (loans) above a certain level (7% under Basel III requirements).

2.2.4 Initial Conditions

The fluctuations in the yields on different debt instruments play a key role in the model of this paper. In particular, through affecting the debt structure of BFs, changes in interest rates have clear implications for different debt markets. The model includes 6 different interest rates whose initial values are presented in Figure 10. The initial level of these rates are chosen in a way that reflects the actual values (were possible), the relative riskiness of debt instruments, and the possible portfolio rebalancing. First, the risk free rate ($r_{RF}$) and gilts rate are set to the actual levels of BoE policy rate (0.5%) and 10-year gilts rate (4%) just before the launch of APP. Second, risk premiums on different types of bank loans are arbitrarily selected given that loans to SMEs are risker than mortgages which, in turn, are risker than loans to BFs. Moreover, since corporate bonds represent a good substitute of gilts, it is reasonable to assume the rate
on bonds follows gilts rate fluctuations whether they are resulted from the changes in risk-free rate or gilts risk premium. Lastly, the fact that the corporate bonds represented 32.7% of nonfinancial corporations’ total debt of in 2009 Q1 indicates that the cost of these bonds was higher than the cost of bank loans. Thus, the risk premium on BF’s bonds is set to 2% to make interest rate on these bonds higher than interest rate on BF’s loans.

**Figure 10: Initial Values of Interest Rates**

<table>
<thead>
<tr>
<th>Interest Rate</th>
<th>Initial Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>risk free rate ($r_{RF}$)</td>
<td>0.5%</td>
</tr>
<tr>
<td>government gilts rate ($r_{G}$)</td>
<td>4%</td>
</tr>
<tr>
<td>interest rate on mortgages ($r_{H}$)</td>
<td>7% ($r_{RF} + 6.5%$)</td>
</tr>
<tr>
<td>interest rate on BF’s loans ($r_{BF}$)</td>
<td>5.5% ($r_{RF} + 5%$)</td>
</tr>
<tr>
<td>interest rate on BF’s security debt ($r_{S}$)</td>
<td>6% ($r_{RF} + 2%$)</td>
</tr>
<tr>
<td>interest rate on SMEs loans ($r_{SME}$)</td>
<td>8.5% ($r_{RF} + 8%$)</td>
</tr>
</tbody>
</table>

1 BoE’s policy rate. (Source: Bank of England [http://www.bankofengland.co.uk](http://www.bankofengland.co.uk))
2 Median yield on 10-year gilts in 2008 Q4 (Source: DataStream®)

**2.3 Agents Behaviours**

This section demonstrates the responses of the model agents to the developments in the surrounding environment on the one hand and the actions of each other on the other. According to Daines, Joyce and Tong (2012), the first round BoE purchases caused a 100 basis points fall in gilts yields. Hence, the impact of BoE’s APP is introduced into the model by allowing gilts rate to decrease by 2.5 basis points each period. This fall in gilts yield accompanied with fixed risk free rate (imitating the fixed policy rate) result in changes in the relative cost of corporate bonds and consequently have significant implications for BF’s.

**2.3.1 Households Behaviour**

The model assumes that HHs incomes grow at 0.275% each month in line with inflation between March 2009 and March 2013 where average annual inflation rate in the UK was 3.3% during that period. It also assumes that HHs keep their expenditure habits of spending 70% of income on consumption unchanged. The remaining 30% of income adds to household cash which is used to pay the mortgage obligations (mortgage principal and interest) and to cover the deposit if a new mortgage is obtained. In every period, each household chooses whether it wants to buy a new house and comes with a positive outcome with a
probability that depends on its current home ownership status; that is, when a household is a first time buyer (or has no housing wealth), the urgency to buy a home is greater. To accommodate this, the model assume that a household decides it wants to buy a house with probability of 20% if it has at least one house and 30% if it has none. Once the household elects to buy a house, it applies for a mortgage to finance the purchase from its bank. The household application will be successful if it meets the minimum requirements employed by the banks in the model. To obtain a new mortgage, banks require the applying household to have at least twice the down payment or the deposit (5% of house price), no more than 3 mortgages, and sufficient income to meet mortgage obligations including those related to the new mortgage. Household income would be sufficient if mortgage payment in the coming month (including the amount related to the new mortgage) represents no more than 40% of that income. Altogether, the components of a household balance sheet in any period $t$ are given by the following set of equations:

$$\text{Income}_t = \text{Income}_{t-1} \times \left(1 + \frac{0.033}{12}\right)$$

(1)

$$\text{Housing}_t = \text{Housing}_{t-1} + \frac{1}{0.95} \times \text{New Mortgage}_t$$

(2)

$$\text{Liquidity}_t = \text{Liquidity}_{t-1} + 0.3 \text{Income}_t - \frac{0.05}{0.95} \times \text{New Mortgage}_t - \text{Mortgage Payment}_t$$

(3)

$$\text{Mortgage Payment}_t = \text{Principal Payment}_t + \text{Interest}_t$$

(4)

$$\text{Principal Payment}_t = \frac{0.95}{360} \times \text{Number of Mortgages}_t \times \text{House Price}_t$$

(5)

$$\text{Interest}_t = \frac{r_H(t-1)}{12} \times \text{Mortgages}_{t-1}$$

(6)

$$\text{Mortgage Available}_t = \begin{cases} 1 & \text{if } \text{Liquidity}_{t-1} \geq 2 \times 7,470 \text{ and } \text{Mortgage Payment}_{t+1} \leq 0.4 \times \text{Income}_t \\ 0 & \text{Otherwise} \end{cases}$$

(7)

$$\text{New Mortgage}_t = \begin{cases} 141,930 & \text{if Household Wants to buy = 1, Mortgage Available}_t = 1 \\ 0 & \text{Otherwise} \end{cases}$$

(8)

$$\text{Mortgages}_t = \text{Mortgages}_{t-1} - \text{Principal Payment}_t + \text{New Mortgage}_t$$

(9)

$$\text{Equity}_t = \text{Housing}_t + \text{Liquidity}_t - \text{Mortgages}_t$$

(10)
2.3.2 Big Firms Behaviour

The model assumes that over the simulation period BFs keep the size of physical capital and total debt unchanged, issue no new equity, and maintain a constant annual operating profit (i.e. profit before interest) to total assets ratio of 10%. In each period, a big firm compares between bank borrowing and security debt to decide whether to change the composition of its debt financing or not. The comparisons here are based on the relative interest costs of the two sources and a relative desirability factor that makes one source preferred to the other at certain economic conditions. Generally, bank loans are shorter in maturity than corporate bonds and tend to carry more flexible interest rates. Therefore, it is feasible to say that firms would prefer bank borrowing to security debt in booms when interest rates are relatively high and vice versa in recessions when the rates are low. When interest rates are relatively high, firms prefer bank loans since they represent shorter commitments whose interest cost would decrease faster than the interest cost of security debt. Inversely, lower interest rates make security debt more attractive to firms since they can enjoy fixed but low interest rates for a longer periods of time compared to bank borrowing. Thus, since interest rates at the start of the simulation period are relatively low, BFs will respond to decreases in bonds interest rate ($r_S$) when it becomes equal to the interest rate on bank borrowing ($r_{BF}$) by issuing more bonds and use the proceeding to pay back a part of their bank loans. In particular, once $r_S$ becomes smaller than $r_{BF}$, BFs in every period replace a fraction of $(0.015 + r_{BF} - r_S)^2$ of its current bank loans by security debt (equations 14 & 15). Accordingly, the components of a big firm balance sheet in any period $t$ can be given as follows:

\[
\text{Physical Capital}_t = \text{Physical Capital}_{t-1}
\]

\[
\text{Operating Profit}_t = 0.10 \times (\text{Physical Capital}_{t-1} + \text{Liquidity}_{t-1})
\]

\[
\text{Liquidity}_t = \text{Liquidity}_{t-1} + \text{Operating Profit}_t - r_{S(t)} \cdot \text{Bonds}_{t-1} - r_{BF(t)} \cdot \text{Loans}_{t-1}
\]

\[
\text{Loans}_t = \begin{cases} 
\text{Loans}_{t-1} & \text{if } r_S \geq r_{BF} \\
\text{Loans}_{t-1} \times \left(1 - (0.015 + (r_{BF} - r_S))^2\right) & \text{if } r_S < r_{BF}
\end{cases}
\]

\[
\text{Bonds}_t = \begin{cases} 
\text{Bonds}_{t-1} & \text{if } r_S \geq r_{BF} \\
\text{Bonds}_{t-1} + (0.015 + (r_{BF} - r_S))^2 \times \text{Loans}_{t-1} & \text{if } r_S < r_{BF}
\end{cases}
\]

\[
\text{Equity}_t = \text{Physical Capital}_t + \text{Liquidity}_t - \text{Loans}_t - \text{Bonds}_t
\]
2.3.3 Banks Behaviour

As mentioned earlier, banks in the model are able to grant unlimited amount of loans but have to commit to capital adequacy rules that require them to finance a certain proportion of their risk weighted assets (loans) using equity capital. It is sensible here to say that capital adequacy requirements will not affect banks’ lending capacity when economic climate is good because of the relatively lower risks associated with different loans and higher ability to raise equity capital from internal and external resources. However, when the economy is unwell, the riskiness of most loans increases especially business loans provided to financially fragile customers like SMEs, and the possibility of raising external equity capital becomes limited. In other words, while banks are willing to grant (renew) loans to almost every suitable customer in good economic conditions, they tend to be very cautious in providing financing to risky customers when the economy is unwell. In terms of riskiness, business loans to BFs represent the safest asset in bank balance sheet and loans to SMEs are the most risky, whereas mortgages include average risks. Therefore, since the economic conditions -the model imitates- are not good and BFs start to decrease their bank borrowing -as a result of the drop the cost of corporate bonds mentioned earlier-, banks -motivated by the risker asset pools- start to restructure their asset portfolios towards less loans to SMEs and more mortgages. The tendency to reduce business loans to SMEs is assumed to grow as BFs replace more and more of the bank loans with security debt (equation 20).

2.3.4 SMEs Behaviour

Similar to BFs, SMEs have a constant but lower annual operating profit to total assets ratio of 5%, and keep the size of physical capital fixed over the simulation period. Yet, SMEs can’t -to large extent- control their debt financing -like BFs- since the single source of this financing is bank loans whose size depends on solely banks’ will to renew or extend current credit facilities to these firms. Additionally, the model assumes that SMEs can’t raise further their external equity financing during the simulation period. As shown above, when BFs cut their bank borrowing, SMEs face declining amounts of credit facilities they receive from banks, and the bigger the reduction in BFs bank borrowing, the stronger will be the drop in loans to SMEs. In particular, the model assumes that once BFs start to replace bank loans with bonds, the amount of loans
granted to each SME drops by \((0.015 + r_{BF} - r_5)^2\) in every period. Consequently, the components of a SME balance sheet in a given period \(t\) are as follows:

\[
Physical\ Capital_t = Physical\ Capital_{t-1} \tag{17}
\]

\[
Operating\ Profit_t = 0.05 \times (Physical\ Capital_{t-1} + Liquidity_{t-1}) \tag{18}
\]

\[
Liquidity_t = Liquidity_{t-1} + Operating\ Profit_t - r_{SME(t)} \cdot Loans_{t-1} - Loans_{t-1} + Loans_t \tag{19}
\]

\[
Loans_t = \begin{cases} 
Loans_{t-1} & \text{if } r_5 \geq r_{BF} \\
Loans_{t-1} \times \left(1 - (0.015 + (r_{BF} - r_5))^2\right) & \text{if } r_5 < r_{BF} 
\end{cases} \tag{20}
\]

\[
Equity_t = Physical\ Capital_t + Liquidity_t - Loans_t \tag{21}
\]

3. Simulation Results

As stated earlier, the model in this paper covers a period of 50 months and mimics the interaction between different agents and the responses of these agents to the developments in debt markets. The simulation has produced the results displayed in the Figures 11-14. These results present similar trends to the actual data especially with respect to mortgages and total bank lending which shows a significant drop in the second half of the simulation period once the fall in gilts (and hence bonds) yields starts affecting the debt structure of BF towards less bank loans and more security debt. Banks respond to these changes by expanding mortgages in a faster rate and cutting the amount of risker loans to SMEs in a way that maintains profitability and commits to capital adequacy requirements.

Figure 11: Households Mortgage Indebtedness
4. Conclusion

Increasing bank lending is one of the main goals of BoE’s APP launched early in 2009. Yet, ONS sectoral financial accounts data shows that although bank lending to households has been expanding since 2009,
total bank lending witnessed a noticeable drop driven by the falling lending to businesses. To explain this decrease in bank lending, this paper introduces a baseline ACE model which contains four types of agents - 1,000 households (HHs), 25 big firms (BFs), 300 small and medium enterprises (SMEs) and 10 banks - and mimics the interaction between these agents in different credit markets. HHs in the model own houses and hold cash with banks, and finance these assets using a mixture of mortgages and equity (net worth).

A household can expand asset holding by saving a part of its income and/or obtain a mortgage from its preferred bank. Moreover, both firm types (BFs and SMEs) utilize a combination of physical capital and cash -financed by equity and debt capital- to make profit. Yet, while SMEs are restricted to bank borrowing as the sole source of debt financing, BFs can choose between bank loans and issuing bonds to raise debt capital. Lastly, banks hold the cash of the other agents and provide debt financing to these agents in the form of mortgages (granted to HHs) and business loans (to BFs and SMEs).

The baseline model was anchored to the actual values of several variables -such as homeownership statistics and nonfinancial firms leverage ratio- around the time of APP launch, then simulated for 50 periods (months). Simulation results present similar trends to the actual data especially for mortgages and total bank lending. In the early periods, the fast growing mortgages expand total bank lending. However, once BFs start to exchange part of their bank borrowing with security debt as a result of the lower gilts (because of APP) and hence corporate bonds yields, the size of total bank lending start to fall. A possible explanation of these trends is that the fall in gilts yield and then corporate bonds yield -through portfolio rebalancing effect- encourages BFs to adjust their debt financing towards less bank borrowing and more security debt. The decrease in BFs loans -which represent the safest asset in bank portfolios- increases the riskiness of banks asset pools, and hence induce banks to invest more in the safer asset (mortgages) and less of the riskier asset (loans to SMEs).
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Appendices:

A1- Simulated Distribution (Monthly Income of HHs)

A2- Matlab Code:

clc
clear all

colour = 'r';

%% Parameters
T = 50;                          % Simulation period in months.
DTV = 0.05;                      % the proportion of the house value a household has to put as a down payment (deposit in the UK).

%% The Size of Agent Populations
NrHHs = 1000;                    % the number of households.
NrBFs = 25;                      % the number of big firms.
NrSMEs = 229;                    % the number of small and medium enterprises.
NrBanks = 10;                    % the number of banks.

%% Initial Values
rG(1) = 0.04;                    % interest rate on government gilts.
rH(1) = 0.07;                    % interest rate on mortgages.
rRF(1) = 0.005;                  % risk-free interest rate.
rBF(1) = rRF(1) + 0.05;          % interest rate on big firms bank loans.
rS(1) = rG(1) + 0.02;            % interest rate on big firm bonds.
rSME(1) = rRF(1) + 0.08;         % interest rate on small and medium enterprises bank loans.
HousePrice(1) = 149400;         % average house price.
%% House ownership status
% only 64% of UK households live in owned homes calibrated using ONS data.
Household.NrHouses(1,:) = round(rand(1,NrHHs)*4)
for hh=1:NrHHs
    if Household.NrHouses(1,hh)==0
        per = 36/100
    else
        per = 16/100
    end
end

%% Household Balance Sheets
% Assets Side
Household.Housing(1,:) = Household.NrHouses(1,:) * HousePrice(1);
Household.Liquidity(1,:) = randi([5000 50000],1,NrHHs);

% Liabilities Side
if Household.Housing(1,:) == 0
    Household.Mortgages(1,:) = 0
else
    Household.Mortgages(1,:) = randi([0 70965],1,NrHHs)
end
Household.Equity(1,:) = Household.Housing(1,:) + Household.Liquidity(1,:) - Household.Mortgages(1,:);

%% Household Income
% Household income in the UK follows a lognormal distribution according to IFS.
pd = makedist('Lognormal','mu',7.47515025423602,'sigma',0.662869245249149);
Household.Income(1,:) = random(pd,NrHHs,1);

%% Household Willingness to Buy a Property
Household.WantToBuy(1,:) = round(rand(1,NrHHs)*1)
for hh=1:NrHHs
    if Household.Housing(1,:) == 0
        if Household.WantToBuy(1,hh)==0
            per = 70/100
        else
            per = 30/100
        end
    else
        if Household.WantToBuy(1,hh)==0
            per = 80/100
        else
            per = 20/100
        end
    end
end

%% Household preferred bank
Household.IdxBank = randi(NrBanks,1,NrHHs);

%% Big Firm Balance Sheet
% Assets Side
BF.PhysicalCapital(1,:) = randi([5000000 300000000],1,NrBFs);
BF.Liquidity(1,:) = (0.1283/0.8717) * (BF.PhysicalCapital(1,:));
% liquid assets represent 12.83% of nonfinancial firms total assets in 2009 Q1
% Liabilities Side
BF.Loops (1,:) = 0.3477*(BF.PhysicalCapital(1,:)+BF.Liquidity(1,:));  %
BFs leverage ratio in 2009 Q1 was 51.66% and loans represented 67.3% of total debt
BF.Bonds (1,:) = 0.1689*(BF.PhysicalCapital(1,:)+BF.Liquidity(1,:));    %
BFs leverage ratio in 2009 Q1 was 51.66% and security debt represented 32.7% of total debt
BF.Equity (1,:) = BF.PhysicalCapital(1,:) + BF.Liquidity(1,:) - BF.Loans (1,:)
  - BF.Bonds (1,:);

% Big firm preferred bank
BF.IdxBank = randi(NrBanks,1,NrBFs);

% Small/Medium Firm Balance Sheet
% Assets Side
SME.PhysicalCapital(1,:) = randi([50000 1000000],1,NrSMEs);
SME.Liquidity(1,:) = (0.1283/0.8717) * (SME.PhysicalCapital(1,:)); %
liquid assets represented 12.83% of nonfinancial firms total assets in 2009 Q1

% Liabilities Side
SME.Loans (1,:) = 0.40*(SME.PhysicalCapital(1,:)+SME.Liquidity(1,:));  %
SMEs are less able to use debt financing, hence the leverage ratio is assumed to be 40%
SME.Equity (1,:) = SME.PhysicalCapital(1,:) + SME.Liquidity(1,:) - SME.Loans (1,:);

% Small/Medium firm preferred bank
SME.IdxBank = randi(NrBanks,1,NrSMEs);

% Bank balance sheets
% Assets Side
for b=1:NrBanks
    Bank.TotalMortgages(1,b) = sum(Household.Mortgages(1,find(Household.IdxBank==b)));
    % consistency with households mortgages
end
for b=1:NrBanks
    Bank.BFLoans(1,b) = sum(BF.Loans(1,find(BF.IdxBank==b)));
end
for b=1:NrBanks
    Bank.SMEloans(1,b) = sum(SME.Loans(1,find(SME.IdxBank==b)));
end
% Total Bank Lending:
for b=1:NrBanks
    Bank.TotalLending(1,b) = Bank.TotalMortgages(1,b) + Bank.BFLoans(1,b) +
    Bank.SMEloans(1,b)
    Bank.Liquidity(1,:) = (Bank.TotalMortgages(1,:) + Bank.BFLoans(1,:) +
    Bank.SMEloans(1,:)) * (1/9);  % hyp:
    Liquidity represents 10% of the total assets of a bank
end
% Liabilities Side
for b=1:NrBanks
Bank.Deposits(1,b) = 
sum(Household.Liquidity(1,find(Household.IdxBank==b))) + 
sum(BF.Liquidity(1,find(BF.IdxBank==b))) + 
sum(SME.Liquidity(1,find(SME.IdxBank==b))); 
end
Bank.Equity(1,:) = Bank.Liquidity(1,:)+ Bank.TotalMortgages(1,:) - 
Bank.Deposits(1,:);

%% Interest Rates Dynamics: 
for t=2:T 
rG(t) = rG(t-1) - 0.00025; 
rH(t) = rH(t-1); 
rRF(t) = rRF(t-1); 
rBF(t) = rRF(t) + 0.05; 
rS(t) = rG(t) + 0.02; 
rSME(t) = rRF(t) + 0.08; 
end

%% Balance Sheet Developments: 
for t = 2:T
  %% 1- Big Firms Balance Sheets: 
  % Big Firm Physical Capital: 
  BF.PhysicalCapital(t,:) = BF.PhysicalCapital(t-1,:);
  % Big Firm Debt Financing: 
  if rS(t)<rS(t-1) && rS(t)<rBF(t) 
    BF.Bonds(t,:) = BF.Bonds(t-1,:) + ((0.015 + (rBF(t) - rS(t)))^2) * 
    BF.Loans(t-1,:); 
    BF.Loans(t,:) = (1 - (0.015 + ((rBF(t) - rS(t))))^2) * BF.Loans(t-1,:); 
  else 
    BF.Bonds(t,:) = BF.Bonds(t-1,:); 
    BF.Loans(t,:) = BF.Loans(t-1,:); 
  end
  % Big Firm Profits
  BF.Profit(t,:) = (0.10/12) * (BF.PhysicalCapital(t-1,:) + BF.Liquidity(t-1,:)); 
  the return on total assets is 10% for the big firms 
  % Big Firm Liquidity:
  BF.Liquidity(t,:) = BF.Liquidity(t-1,:) + BF.Profit(t,:) - rS(t) * 
  BF.Bonds(t-1,:) - rBF(t) * BF.Loans(t-1,:);
  % Big Firm Equity:
  BF.Equity(t,:) = BF.PhysicalCapital(t,:) + BF.Liquidity(t,:) - BF.Loans(t,:) - BF.Bonds(t,:); 

  %% 2- Small & Medium Enterprises Balance Sheets: 
  % SME Physical Capital:
  SME.PhysicalCapital(t,:) = SME.PhysicalCapital(t-1,:);
  % SME Banks Borrowing:
  if sum(BF.Loans(t,:)) < sum(BF.Loans(t-1,:)) 
    SME.Loans(t,:) = SME.Loans(t-1,:) * (1 - (0.015 + (rBF(t) - 
    rS(t)))^2); 
  else 
    SME.Loans(t,:) = SME.Loans(t-1,:); 
  end
  % SME Profit:
SME.Profit(t,:) = (0.05/12) * (SME.PhysicalCapital(t-1,:) + SME.Liquidity(t-1,:));

% hyp: the return on total assets is 5% for the small and medium enterprises
% SME Liquidity:
SME.Liquidity(t,:) = SME.Liquidity(t-1,:) + SME.Profit(t,:) - rSME(t) * SME.Loans(t-1,:) - (SME.Loans(t-1,:) - SME.Loans(t,:));

% SME Equity:
SME.Equity(t,:) = SME.PhysicalCapital(t,:) + SME.Liquidity(t,:) - SME.Loans(t,:);

%% 3- Households Balance Sheets:
% House Prices
HousePrice(t) = HousePrice(t-1)*(1+0.00255178010441925);
% House prices monthly growth rate between 2009 and 2013 was 0.255178%
% Household Income:
Household.Income(t,:) = Household.Income(t-1,:) * (1 + 0.033/12);
% Household Mortgage Payments, New Mortgages, and Total Mortgages:
% Principal Payback:
for hh=1:NrHHs
    if Household.Mortgages(t-1,hh) <= 0
        Household.PrincipalPayment(t,hh) = 0
    else
        if Household.Mortgages(t-1,hh) <= (1-DTV)* HousePrice(t)/360
            Household.PrincipalPayment(t,hh) = (1-DTV)* HousePrice(t)/360
        else
            if Household.Mortgages(t-1,hh) <= 2 * (1-DTV)* HousePrice(t)/360
                Household.PrincipalPayment(t,hh) = 2 * (1-DTV)* HousePrice(t)/360
            else
                if Household.Mortgages(t-1,hh) <= 3 * (1-DTV)* HousePrice(t)/360
                    Household.PrincipalPayment(t,hh) = 3 * (1-DTV)* HousePrice(t)/360
                else
                    Household.PrincipalPayment(t,hh) = 4 * (1-DTV)* HousePrice(t)/360
                end
            end
        end
    end
end

% Total Mortgage Payments (Interest & Principal):
for hh=1:NrHHs
    if Household.Mortgages(t-1,hh) > 0
        Household.MortgagePayment(t,hh) = Household.PrincipalPayment(t,hh) + (rH(t-1)/12)* Household.Mortgages(t-1,hh)
    else
        Household.MortgagePayment(t,hh) = 0
    end
end
% Household Balance Sheets continue Below...

%% 4- Bank Balance Sheets:
% Loans to Big Firms:
for b=1:NrBanks
    Bank.BFLoans(t,b) = sum(BF.Loans(t,find(BF.IdxBank==b)));
end
end

% Loans to SMEs:
for b=1:NrBanks
    Bank.SMELoans(t,b) = sum(SME.Loans(t,find(SME.IdxBank==b)));
end

% Bank Balance Sheets Continue Below...

%% 3- Households Balance Sheets Continued
% New Mortgages Availability for a Household:
for hh=1:NrHHs
    if Household.Mortgages(t-1,hh) <= 3 * (1-DTV)* HousePrice(t)/360 & (Household.MortgagePayment(t,hh) + (1 + rH(t)) * (1-DTV)* HousePrice(t)/360) <= 0.40 * Household.Income(t,hh) & Household.Liquidity(t-1,hh) >= 2 * 0.05 * (1-DTV)* HousePrice(t)
        Household.MortgageAvailable(t,hh) = 1
    else
        Household.MortgageAvailable(t,hh) = 0
    end
end

% Household Willingness to Buy a Property
Household.WantToBuy(t,:) = round(rand(1,NrHHs)*1)
for hh=1:NrHHs
    if Household.Housing(t-1,:) == 0
        if Household.WantToBuy(t,hh)==0
            per = 70/100
        else
            per = 30/100
        end
    else
        if Household.WantToBuy(t,hh)==0
            per = 80/100
        else
            per = 20/100
        end
    end
end

% New Mortgages:
for hh=1:NrHHs
    if Household.WantToBuy(t,hh) == 1 & Household.MortgageAvailable(t,hh) == 1
        Household.NewMortgage(t,hh) = HousePrice(t) * (1-DTV)
    else
        Household.NewMortgage(t,hh) = 0
    end
end

% Total Mortgages:
Household.Mortgages(t,:) = Household.Mortgages(t-1,:) - Household.PrincipalPayment(t,:) + Household.NewMortgage(t,:);

% Household Housing Wealth:
Household.Housing(t,:) = Household.Housing(t-1,:) + (1/(1-DTV)) * Household.NewMortgage(t,:);

% Household Liquidity:
Household.Liquidity(t,:) = Household.Liquidity(t-1,:) - (rH(t-1)/12)* Household.Mortgages(t-1,:) - Household.PrincipalPayment(t,:) - (DTV/(1-DTV)) * Household.NewMortgage(t,:) + 0.30 * Household.Income(t,:);

% Household Equity:
Household.Equity(t,:) = Household.Housing(t,:) + Household.Liquidity(t,:) - Household.Mortgages(t,:);

%% 4- Bank Balance Sheets Continued

% Total Mortgages:
for b=1:NrBanks
    Bank.TotalMortgages(t,b) = sum(Household.Mortgages(t,find(Household.IdxBank==b)));
end
% Total Bank Lending:
for b=1:NrBanks
    Bank.TotalLending(t,b) = Bank.TotalMortgages(t,b) + Bank.BFLoans(t,b) + Bank.SMELoans(t,b);
end
% Bank Profit:
for b=1:NrBanks
    Bank.Profit(t,b) = sum((rH(t-1)/12)*Household.Mortgages(t-1,find(Household.IdxBank==b))) + sum((rBF(t-1)/12)*BF.Loans(t-1,find(BF.IdxBank==b))) + sum((rSME(t-1)/12)*SME.Loans(t-1,find(SME.IdxBank==b)));
end
% Bank Liquidity:
for b=1:NrBanks
    Bank.Liquidity(t,b) = Bank.Liquidity(t-1,b) + sum(Household.MortgagePayment(t,find(Household.IdxBank==b)) + sum((rBF(t-1)/12)*BF.Loans(t-1,find(BF.IdxBank==b))) + sum((rSME(t-1)/12)*SME.Loans(t-1,find(SME.IdxBank==b))));
end
% Bank Deposits:
for b=1:NrBanks
    Bank.Deposits(t,b) = sum(Household.Liquidity(t,find(Household.IdxBank==b)) + sum(BF.Liquidity(t,find(BF.IdxBank==b)) + sum(SME.Liquidity(t,find(SME.IdxBank==b))));
end
% Bank Equity:
Bank.Equity(t,:) = Bank.Liquidity(t,:) + Bank.TotalMortgages(t,:) - Bank.Deposits(t,:);

end

%% Simulations and Results:

font_sz = 12;
figure(21);
subplot(2,1,1); hold on; grid on
plot(sum(Bank.TotalLending,2),colour)
ylabel('Total Bank Lending', 'fontsize', font_sz)
xlabel('months', 'fontsize', font_sz)
figure(22);
subplot(2,1,1); hold on; grid on
plot(sum(Bank.TotalMortgages,2),colour)
ylabel('Total Mortgages','fontsize',font_sz)
xlabel('months','fontsize',font_sz)

figure(23);
subplot(2,1,1); hold on; grid on
plot(sum(Bank.BFLoans,2),colour)
ylabel('Loans to BF','fontsize',font_sz)
xlabel('months','fontsize',font_sz)

figure(24);
subplot(2,1,1); hold on; grid on
plot(sum(Bank.SMELoans,2),colour)
ylabel('Loans to SMEs','fontsize',font_sz)
xlabel('months','fontsize',font_sz)