# Mortgage Cash-flows and Employment

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**Abstract**

This paper quantifies the impact of the cash-flow channel of monetary policy on employment by combining novel micro datasets with near-universal coverage. When policy interest rates fall, families with a mortgage spend the extra cash-flow in their local economy and this increases labor demand. Overall, a reduction in mortgage payments of £1,000 per household led to a 0.3 percentage point increase in locally non-tradable employment growth over three years of the Great Recession, with the most pronounced effects in the restaurant sector. Spatial variation in labor and mortgage market structures leads to regional heterogeneity in the traction of monetary policy.

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# 1 Introduction

Monetary policy has redistributive consequences through a number of channels, but little is understood about how the transmission mechanism propagates through different regions or industries. One channel that has recently attracted attention operates through the shock to household disposable income that results from the interaction of policy interest rates and mortgage debt. This cash-flow effect has been considered by policymakers for some time (e.g., Bernanke (2007)) but there has been little attempt to quantify how it might directly affect employment via increases in local spending and labor demand. I fill this gap by combining multiple datasets with near-universal coverage to investigate the importance of the cash-flow effect on employment and firm heterogeneity.

A recent strand of literature has explored the transmission of macroeconomic shocks across the economy in the context of debt, both for households (e.g., Verner and Gyongyosi (2018); Cloyne et al. (2018) and Beraja et al. (2018)) and firms (e.g., Giroud and Mueller (2019) and Gürkaynak et al. (2019)). I exploit regional heterogeneity in the concentration of adjustable-rate mortgages resulting from the timing of mortgaging activity to identify the effect of neighborhood cash-flow shocks on locally non-tradable employment during the Great Recession. The 400 basis point reduction in policy interest rates between October 2008 and March 2009 reduced mortgagors' repayments at different points over the next few years. Neighborhoods with a large share of adjustable-rate mortgages in 2008 soon received substantial favorable cash-flow shocks, which slackened liquidity constraints and boosted local spending and employment.

The central analysis is split into two stages. I first model the evolution of around five million mortgage payment flows to estimate the household-level change in cash flows that followed from the systematic and unexpected easing of monetary policy in the fall of 2008. I go on to define locally non-tradable establishments as those generating revenues from nearby

customers and group households into neighborhoods.[1] I then exploit the staggered timing of interest rate pass-through to estimate the relationship between changes in cumulative neighborhood-level cash-flow shocks in the nine quarters after the dramatic fall in interest rates, and the growth of locally non-tradable employment between 2007 and 2010.

For many mortgaged households, the direct effect of monetary policy on household finances was substantial. I document that the average household on a fixed-rate mortgage in the middle of 2008 experienced a reduction in mortgage repayments equivalent to 2.6% of their gross income during the two years after policy interest rates reached their 2009 floor. The size of this windfall largely depended on when their mortgage automatically reset to an adjustable rate following the end of their initial fixation period. That was often pre-determined by mortgaging choices in bygone years. In contrast, households on an adjustable-rate mortgage throughout the period of study experienced a total reduction in repayments of around £8,000, equivalent to 5.5% of gross income. Aggregating these windfalls to around 8,000 neighborhoods (so-called *wards* in the UK) provides the variation required to identify the knock-on impact to employment in the local economy.

I find that locally non-tradable establishments in neighborhoods with a large fraction of adjustable-rate mortgagors increased their employment relative to neighborhoods awash with fixed-rate mortgagors. My central estimates suggest that a neighborhood-wide average cash-flow shock of £1,000 per mortgagor was associated with around a 0.3 percentage point (pp) increase in the annual growth of locally non-tradable employment between 2007 and 2010 in that neighborhood. On average, my results suggest that a total cash-flow injection in a neighborhood of around £350,000 saved one locally non-tradable job over that time horizon, which is consistent with estimates of the marginal propensity to consume out of windfalls (e.g., Bunn et al. (2018b); Christelis et al. (2019) and Fagereng et al. (2019)) and salaries in the locally non-tradable sector. The cash-flow effect disappears entirely when an

[1]Locally non-tradable firms and establishments are defined in the spirit of Mian and Sufi (2014), Verner and Gyongyosi (2018) and Giroud and Mueller (2019).

alternative specification is run on manufacturing-sector employment, whose establishments' demand for labor is unlikely to be related to spending by local residents. Comparing locally non-tradable and manufacturing establishments helps to rule out other confounding channels that might be operating, such as labor-supply effects.

Overall, I estimate that between half and two thirds of the employment effect in the locally non-tradable sector came about through establishments boosting staff numbers through the intensive margin of adjustment. The rest of the effect manifested itself via an increased probability of establishment birth, and a decreased probability of establishment death, between 2007 and 2010. The strongest effects I find are for establishments in the auto service and restaurant sector, and there appears to be almost no effect in the retail sector, which accounts for more than half of locally non-tradable employment.

The cash-flow channel of employment varied substantially across the country. In part, this was due to the distribution of mortgagors on different types of contract, which was a key driver for the spatial distribution of neighborhood cash-flow shocks. Moreover, the joint spatial distribution of mortgage and labor market structures led to significant heterogeneity in the traction of conventional monetary policy across the country in the Great Recession. Regions where the local economy was relatively self-contained and employed a large share of people in the locally non-tradable sector enjoyed more of the direct benefits of monetary policy through stronger employment growth. My results suggest that the impact from the overall change in policy rates on total employment growth in the Great Recession varied by up to 0.5pp across neighborhoods. Since both employment and mortgage market structures are likely to vary over time, their joint evolution is important for an up-to-date understanding of the monetary transmission mechanism across regions and industrial sectors.

An important concern is that people who took out fixed and adjustable-rate mortgages were different. In particular, my estimates would be biased upwards if the households more likely to take out adjustable-rate mortgages ended up being more insulated from the eventual

economic slow-down. I show that observable characteristics across interest rate types were relatively similar. Indeed, since fixation periods were short, the choice between fixed and adjustable was often driven by whichever contract had the lowest initial interest rate, perhaps because people were myopic or liquidity constrained. As a result, almost 40% of remortgagors took out both fixed and adjustable-rate contracts at different times in the immediate run-up to the Global Financial Crisis (henceforth, Crisis).

I propose an instrumental variable specification where I construct a *predicted* neighborhood cash-flow shock based primarily on *when* people took out their mortgages in a particular area. Since fixed and adjustable-rate mortgages are priced using information embedded in the yield curve, the yield curve slope shortly before origination was a good predictor of the spread between the benchmark fixed and adjustable-mortgage rates available, and therefore of the type of mortgage households chose. Moreover, short fixes and early repayment fees meant that the majority of transactions in the stock were remortgages, and spaced at regular intervals.[2] That meant the exact timing of many transactions was determined by home-purchase choices several years prior. My instrument therefore combines time variation in the slope of the yield curve with the natural variation in when mortgaging activity occurred to strip out any selection bias in mortgage choices across households. My central results remain unchanged when I use this *predicted* neighborhood cash-flow shock to instrument for the cash-flow shocks neighborhoods actually received.

Another concern is that interest-rate decisions were based on an anticipation of, or reaction to, monetary policy changes. In fact, households were surprised by the large falls in policy rates. Survey evidence shows that only 10% of households in August 2008 expected policy rates to fall substantially in the coming months. And once households had chosen their mortgage contract before the fall of 2008, they were locked in. The turbulence in the UK mortgage market, which accelerated after the failure of Lehman Brothers, restricted

[2]The most common fixed-rate mortgage had a two year initial term, so many households were on a two-year remortgaging cycle.

fixed-rate mortgagors' ability to refinance their contracts in order to benefit from lower interest rates. A combination of high early-repayment fees, lower collateral values and short fixation periods meant that most fixed-rate mortgagors waited for their interest rate to reset rather than actively seeking out a new contract.[3] This led to a staggered cash-flow effect across households and neighborhoods as interest rates automatically reset to lower levels. I estimate that in the UK at most 7% of people on fixed-rate contracts actively refinanced their mortgages in 2009 based on total remortgaging activity during this period. This stands in stark contrast to the US, where remortgaging spiked up following the monetary easing (e.g., Beraja et al. (2018)).

Finally, I need to demonstrate that other channels are not responsible for the regional variation in employment. Parallel employment trends before interest rates fell provides some comfort that my results are not driven by heterogeneous local business cycles and I show that the characteristics of neighborhoods above and below the median predicted cash-flow shock were similar. In addition, I employ an extensive set of neighborhood controls that use establishment data to construct proxies for the level and type of economic activity going in to the Crisis, and the Gross Value Added (GVA) shock that each neighborhood subsequently experienced. I rule out collateral effects by controlling for house prices and house-price changes between the summer of 2008 and the end of 2010. Since businesses did not exhibit time variation in their interest-rate type choices, the employment cash-flow effect I find likely operates through local spending rather than the supply side of the economy.[4]

My work contributes to the growing literature that cements the cash-flow effect via the mortgage market as a key transmission channel of monetary policy. The notion that the structure of the mortgage market might affect the sensitivity of consumption is well established (e.g., Rubio (2011); Calza et al. (2013) and Cloyne et al. (2018)).[5] But there has

[3]UK mortgage interest rates typically increase with the LTV ratio, which ties collateral values to the cost of refinancing. This was especially true after 2008, see Best et al. (2018) for details.

[4]Moreover, the majority of business owners lived in different parts of the country to their establishments, so director mortgage windfalls are ruled out by using spatial variation.

[5]This is consistent with survey evidence that suggests many households who received a cash-flow windfall

recently been renewed attention on the benefits of adjustable-rate contracts, made more important with the observation that changes in disposable income might have large macroeconomic effects (e.g., Violante et al. (2014); Piskorski and Seru (2018); Guren et al. (2018b) and Greenwald (2018)). The challenge has been to quantify the cash-flow effect in terms of macroeconomic variables. There is compelling evidence that cash-flow commitments, i.e. the debt service ratio, are important for household propensity for delinquency (e.g., Fuster and Willen (2013)) and outright default (e.g., Aron and Muellbauer (2016) and Byrne et al. (2017)) but identification in this area is often restricted to a limited part of the mortgage market. I exploit the finely-balanced distribution of fixed and adjustable-rate contracts in the UK to accurately quantify the employment effect of changes in monetary policy through the cash-flow channel.

Identification of the microeconomic effects of monetary policy is often hampered by the endogeneity of an area's characteristics and the causal effect of a change in interest rates. Recent attempts have been made to overcome this by linking individual spending data to household balance sheets (e.g., Cava et al. (2016); Flodén et al. (2017) and Di Maggio et al. (2017)). I combine the loan-level approach with the more aggregated analysis of Mian and Sufi (2014), Di Maggio et al. (2017) and Verner and Gyongyosi (2018) to examine the employment growth of locally non-tradable establishments in the UK and the evolution of household cash-flows immediately surrounding them. The combination of tightly defined neighborhoods and microdata-aggregated controls means I am more confidently able to use cross-sectional variation to infer the causal impact of cash-flow changes on employment. I go on to show that although the mortgage market is important for understanding the monetary transmission mechanism through to employment, so is the make-up of local labor markets.

This paper also contributes to the literature surrounding the redistributive consequences of monetary policy (e.g., Bullard (2014); Selezneva et al. (2015); Ozkan et al. (2016); Coibion

from lower mortgage repayments in 2009 increased consumption (Hellebrandt et al. (2009)). There is also evidence of wider effects of mortgage interest rate pass-through, such as on fertility (Cumming and Dettling (2019).

et al. (2017) and Bunn et al. (2018a)), though the literature on regional heterogeneity is relatively sparse (e.g., Carlino and DeFina (1997), Beraja et al. (2018) and Guren et al. (2018a)). Perhaps the closest complementary paper to this one is work by Luck and Zimmermann (2019), which investigates a similar question for unconventional policy. But the vast bulk of UK mortgage lending is not conducted by regional banks and using mortgage heterogeneity allows identification of a more precise transmission channel. Like Verner and Gyongyosi (2018), the employment effect I identify operates through changes in consumption, albeit more directly from cash flows, so my work complements the early theoretical work of Jackman and Sutton (1982), supported by empirical evidence in Aron et al. (2012), and more recently Auclert (2019).[6] In particular, my results suggest a feedback link between Auclert's *earnings heterogeneity channel* and the *interest rate exposure channel* via the cash-flow effect when locally non-tradable employment is prevalent. In a similar spirit to Beraja et al. (2018), I am able to track which regions are most responsive to interest rates in the short run and go on to capture the direct knock-on effect monetary policy has on locally non-tradable employment.

# 2 Data

## 2.1 Mortgage data

My analysis uses the universe of residential mortgages issued by UK lenders since April 2005, collected by the Financial Conduct Authority (FCA) and distributed in the Product Sales Database (PSD).[7] It contains a wealth of information on property, borrower and lender characteristics at the time of origination. Using these mortgage flows, I construct an estimate

[6] See Calza et al. (2013) and Corsetti et al. (2018) for studies examining heterogeneous effects of monetary policy through the housing channel.

[7] See `https://www.fca.org.uk/data/product-sales-data` for published high-level data. The PSD includes regulated mortgage contracts only, and therefore excludes other regulated home finance products such as home purchase plans and home reversions, and unregulated products such as second charge lending and buy-to-let mortgages.

for the stock of mortgages in July 2008, well before the failure of Lehman Brothers and the internationally coordinated policy interventions in the fall that year. Appendix 10.1 goes through the steps needed to transform the mortgage flows into the stock.[8]

The 5m mortgages in the stock form a large and representative sample of the residential mortgage market in 2008.[9] The UK mortgage market is broadly split into products that have a fixed interest rate at origination and those that have an interest rate linked to the Bank of England's policy rate (Bank Rate).[10] Often referred to as adjustable-rate mortgages in the US, these are more commonly known as variable-rate mortgages in the UK. Mortgage terms tended to be between 25 and 30 years but the periods governing the path of the interest rate (henceforth, initial period) have historically been relatively short in the UK, especially compared to markets such as the US. The two most popular mortgages between 2005 and 2008 were those that had two-year adjustable or two-year fixed interest rates (and a maximum loan-to-value (LTV) of 75%). So although I refer to the latter as *fixed*, they are actually much closer to a *short-run hybrid* mortgage using North American nomenclature. Short initial periods meant that the split between mortgagors on fixed and adjustable rates has always been relatively even.

Following the end of the initial period, interest rates revert to the so-called *Standard Variable Rate* (SVR). This is a mortgagee-set interest rate that loosely follows the path of Bank Rate. Before the Crisis, the spread between the SVR and remortgage interest rates was around 300-400bp (with little variation across lenders), meaning it was usually beneficial for mortgagors to refinance at the end of their initial period (whether on a fixed or adjustable rate). The majority of mortgagors therefore refinanced every two to three years during the Great Moderation.

[8]From 2015 the FCA began publishing the stock of mortgages, making process outlined in Appendix 10.1 much more straightforward for future studies. Data quality are increasing over time.

[9]There are no consistent estimates of the true universe of mortgages at this time but contemporary estimates of the stock suggest my sample is likely to represent around 80-85% of the relevant residential mortgages.

[10]Before 2009 there were a small number of more exotic products such as mortgages with caps and floors, or with an interest rate linked to an alternative interest rate index.

One apparent concern with my stock is that the mortgages missing from the sample were in some way different to the others, biasing the results. In fact, because this study uses cross-sectional variation, bias is only likely to arise if the missing mortgages are somehow unevenly distributed across the country. This seems unlikely for two reasons. First, all lenders are captured in the PSD so there are no regions that under-report because of high exposure to a particular institution. Second, mortgages issued before 2005Q2 would have likely been linked to Bank Rate by 2008 because the flow of long-term fixed-rate contracts has always been very low in the UK. Missing mortgages are discussed more in Appendix 10.1. The proportions of adjustable and fixed-rate mortgages in the summer of 2008 are shown in Figure 1.

[Figure 1 about here.]

I model mortgagor characteristics from the fourth quarter of 2008 through to the end of 2010 and my primary interest is how quarterly repayments responded to the monetary easing at the end of 2008. There are a wide range of mandatory fields in the PSD that have complete coverage of information collected at origination such as the transaction date, location, borrower birth date, loan value, property value, household income and how the interest rate contractually varied over time. Other variables have less than complete coverage, often due to heterogeneous reporting practices of the mortgage lenders. Of these, the most important variable left blank is the the interest rate at origination. Fortunately, the highly competitive nature of the UK mortgage market means that I can accurately model what the likely interest rate would have been. In addition, the dramatic change in interest rates is more important than the level for cross-sectional variation. Appendix 10.2 addresses how I deal with variables that have incomplete coverage in more detail.

The size of the cumulative cash-flow shock mortgagors received depended on which mortgage they got, and when they got it. There are three possible types of borrower on the eve of the monetary easing in October 2008. Borrowers could either be part-way through a fixed-

rate contract; part-way through an adjustable-rate contract; or beyond the initial period (of either type), and therefore on the SVR. The first group experienced little or no immediate cash-flow shock. The second received a substantial, favorable one. But the third group also often experienced a favorable cash-flow shock because the typical SVR fell in lock-step with mortgage rates at origination. As time went on, more and more households benefited from the positive cash-flow boost. Figure 2 shows the evolution of Bank Rate, the two most common (new) mortgage contracts and the SVR.[11]

[Figure 2 about here.]

## 2.2 Employment data

The main source of employment data is the Business Structure Database (BSD), which contains information for over two million companies registered in the UK. The BSD is compiled as an annual snapshot from the Interdepartmental Business Register (IDBR), which requires firms to report information at the enterprise and establishment level. Since the IDBR is based on Her Majesty's Revenue and Customs tax data, it captures the universe of economically active firms in the UK that are registered for income tax purposes. An enterprise is defined as the smallest combination of legal units that have a degree of autonomy from an enterprise group and can therefore be thought of as the overall business or firm. Enterprises are made up of one or more establishments, or local units, such as individual shops or restaurants. Businesses are required to report turnover at the enterprise level and employment at the establishment level, as well as geographic information for both.

To identify the effects of cash-flow shocks this paper follows Mian and Sufi (2014) and Giroud and Mueller (2019) in categorizing firms into *locally* non-tradable and manufacturing

[11] Deposit interest rates fell a similar amount at the end of 2008 but the overall offsetting cash-flow effect was small because household liabilities often dwarfed deposit assets. The second wave (2008-2010) of the UK Wealth and Assets Survey shows that the median mortgagor owed around £70,000 on their mortgage but only had around £1,000 in savings. Figure 2 shows that the SVR fell less than Bank Rate and so the cash-flow shock was larger for mortgagors on adjustable-rate contracts within their contractual maturity. This is taken account of in the cash-flow modeling.

establishments.[12] The original classification for the US is based on a combination of international trade data, geographical concentration as measured by the geographical Herfindahl index and an intuitive sense of which industries respond most to local demand. An equivalent definition in the UK requires a mapping from the four-digit North American Industrial Classification System (NAICS) to the two-digit Standard Industrial Classification (SIC) system used in most of Europe. While the exact mapping between the two systems at different points in time at a very granular level is far from straightforward, the relatively high-level categories used for this analysis in the time period of interest match up almost exactly as can be seen in the first table in Appendix 10.3.[13] The 25 locally non-tradable and 67 manufacturing four-digit NAICS-12 industries therefore map into 13 and 50 SIC-03 groups, respectively, for this study.

Data from the National Transport Survey (see Department for Transport (2016)) suggest that demand for locally non-tradable purchases is relatively tightly defined. Across England, the average shopping excursion is 7km and makes up a fifth of total trips, though average journeys are two thirds shorter in London and presumably substantially longer in more rural parts of the country.[14] To reflect these patterns, the baseline specification separates the England and Wales into around 8,000 wards, which contain around 5,000 people each. These are a subset of the 343 local authorities and 12 regions.

[12]On the whole, in the locally non-tradable sector, all establishments belonging to an enterprise are in the same two-digit sic code. Results are similar when splitting by establishments within a homogeneous and multi-sic code enterprise.

[13]For example, the NAICS 2012 category of *Automobile dealers* (4411) maps into the SIC 2003 group of *Sales of motor vehicles* (501).

[14]This compares with the average commute within England for work purposes of a little more than 32km. Distances have been increasing marginally over time as household access to cars has increased but there is little evidence to suggest that the number of shopping trips has been falling in any meaningful way, despite the rise of internet transactions.

# 3 Research Design

## 3.1 Baseline Strategy

My empirical strategy tests to what extent cash-flow shocks support consumption and its knock-on effect to local employment.[15] Between the fall of 2008 and early spring of 2009 the Bank of England cut its policy interest rate from 4.5% to 0.5%. Such an unprecedented monetary easing mitigated the shock to consumption and employment from the ongoing decline in economic activity and house prices. But even if all households benefited from the support to asset values and their net wealth, only those on adjustable-rate mortgages benefited from an immediate decrease in mortgage payments.[16] This paper exploits regional heterogeneity in the timing of when households received this substantial cash-flow boost. The higher the proportion of households on an adjustable-rate mortgage in the summer of 2008, or transitioning to one soon after rates fell, the more we might expect an increase in spending on local goods and services relative to areas with a large number of fixed-rate mortgages. This relative difference in consumption should have translated into a relative difference in employment growth at these establishments to the extent that firms adjust their labor inputs in response to demand shocks.[17]

The heart of this study uses the spatial variation in the timing of the cash-flow shock mortgagors received at the end of 2008 to explain subsequent changes in locally non-tradable employment. Specifically, as shown in the schematic in Figure 3, I estimate the stock of mortgages as of July 2008. Bank Rate was initially reduced in October 2008 but I take the stock further back to the summer to exclude those who chose their mortgage type based on the unfolding adverse economic conditions. According to the Bank of England's *Public*

[15] By using spatial variation, this work can be thought of as the cash-flow analogue to work such as Nakamura and Steinsson (2014), Dupor and Guerrero (2017) and Verner and Gyongyosi (2018).

[16] Byrne et al. (2017) exploit the difference between SVR mortgages and (policy rate) tracker mortgages for the Irish mortgage market. In the UK the policy interest rate also fell further than the SVR but the difference was less sharp.

[17] Of course, another form of adjustment is to shut down entirely or to start a new establishment in areas where there is judged to be sufficient demand. This is explored in later sections.

*Attitudes to Inflation* survey, in August 2008 only 10% of people thought interest rates were likely to fall over the next twelve months.[18] I then model the loan-level cash flows from 2008Q3 to 2010Q4 and define the cash-flow shock as the change in mortgage payments relative to the counterfactual payments had interest rates not fallen over the intervening nine quarters.[19] Finally, I compare the neighborhood cash-flow shocks to the three-year change in locally non-tradable employment, between April 2007 and April 2010.[20]

[Figure 3 about here.]

Previous studies such as Di Maggio et al. (2017) have aggregated mortgage characteristics and changes in employment to relatively small contiguous administrative boundaries such as zip codes or counties. My preferred specification aggregates employment and mortgage characteristics to *wards*, which are a subset of local authorities and contain around 5,000 households. Following Davis et al. (2007), the main outcome variable is $e_i^{10-07}$, which represents the percentage change in locally non-tradable employment in ward $i$ between April 2007 and April 2010. Henceforth, I refer to these as my neighborhood regressions. This growth definition is especially helpful when turning to establishment-level regressions later on as the measure is bounded above and below to allow for the possibility of firms shutting down entirely.

$$e_i^{10-07} = 2 \times \frac{E_{i,2010}^{NT} - E_{i,2007}^{NT}}{E_{i,2010}^{NT} + E_{i,2007}^{NT}} \tag{1}$$

After modeling the likely trajectory of every mortgagor's cash flows, I calculate the average cash-flow shock for each neighborhood. In Equation 2 the household cumulative cash-flow shock is the sum of the quarterly cash-flow shocks, which are defined as the difference between the modeled quarterly mortgage payment following the fall in Bank Rate, $p_n^t$, and the

[18] In November 2008 that figure had risen to 39%. See question 6 in the Inflation Attitudes Survey at https://www.bankofengland.co.uk/statistics/research-datasets.

[19] This window makes most sense in terms of when spending could affect the employment decisions I study. The results are quantitatively similar for different length windows.

[20] To the best of the ONS' knowledge, the vast majority of the annual employment data match closely with the financial-year dates reported.

modeled quarterly payment assuming Bank Rate had not changed, $\tilde{p}_n^t$, for each mortgagor, $n$, at time, $t$. The average (sterling-amount) cash-flow shock for neighborhood $i$ is the cumulative cash-flow shock averaged across all mortgagors in the neighborhood, $N_i$.

$$\overline{\Delta C}_i = \frac{1}{N_i} \sum_{n=1}^{N_i} \sum_{t=2008Q3}^{T=2010Q4} p_n^t - \tilde{p}_n^t \quad \forall\, n \in i \tag{2}$$

I can then run a specification that follows the spirit of Mian and Sufi (2014).

$$e_i^{10-07} = \alpha + \beta \times \overline{\Delta C}_i + \gamma_j + \delta \times X_i + \varepsilon_i \tag{3}$$

The baseline specification is a regression of employment growth on the average cash-flow shock with fixed effects for region $j$.[21] Identification in this regression comes from variation across neighborhoods within a particular region and $\beta$ yields the percentage point change in locally non-tradable employment growth for each additional £1,000 of mortgage payment reduction per mortgagor. All regressions are weighted by neighborhood employment and clustered by local authority.[22]

In some specifications I include a vector of neighborhood-specific controls, $X_i$, such as loan-to-income (LTI) ratio, change in house prices and change in local gross-value added (GVA) (excluding wholesale and retail trade).[23] These controls typically use the estimated stock of mortgages and establishment employment data, so accurately capture the characteristics of mortgagors and economic conditions in each neighborhood (see Table 4). The combination of geographic accuracy and near-complete coverage of mortgage data for the regression controls is vital for the causal interpretation of $\beta$ in this OLS regression.

[21] There are twelve regions in the UK and ten in England and Wales.

[22] There are 390 local authorities in the UK and 343 in England and Wales.

[23] Due to data limitations, house price controls are constructed at the local-authority level. The change is house prices and GVA is measured between mid 2008 and the end of 2010.

## 3.2 Identification Challenges

A key identification assumption that spans this research design is that households with adjustable-rate mortgages increased their consumption because they were fortunate enough to receive a cash-flow shock rather than because they differed in other ways to fixed-rate mortgagors. In addition, business employment responses were only driven by changes in relative demand rather than regional heterogeneity in the business cycle.

The first concern regarding identification is that some households might have switched between fixed and adjustable-rate mortgages after the fall in interest rates. This could lead to biased estimates if the propensity to switch mortgages in response to the fall in rates was correlated with mortgagor characteristics. In fact, this active leakage was very small as remortgaging activity fell dramatically following the collapse of Lehman Brothers. As collateral values fell at the end of 2008, mortgage lenders withdrew from the once-active remortgage market. Even if households were able to remortgage in response to falling rates, high early repayment fees in the UK disincentivised those on fixed-rate mortgages to break their contract early. Moreover, lower collateral values and suppressed lender tolerance for high-LTV mortgages meant that refinancing interest rates stayed stubbornly high for many households.

[Figure 4 about here.]

Figure 4 shows how the number of remortgages per month fell by around 75% by the start of 2009. Even if all remortgages over the next twelve months were fixed-rate mortgagors keen to refinance, that only accounts for around 7% of the stock of mortgages used in the main regressions.[24] This subdued refinancing activity stands in stark contrast to the US where remortgages spiked up following the fall in interest rates as those on long term fixed-rate mortgage contracts took advantage of the lower rates. In the UK, the SVR was often an attractive alternative to remortgaging. Relatively short fixation periods meant that most

[24]There were also around 400,000 home movers during this period.

households on fixed-rate mortgages preferred to wait for their contract to roll off and move on to the SVR to benefit from lower interest rates.

Rather than a threat to identification, I can exploit this passive leakage between mortgage types because the exact point at which people rolled on to the adjustable rate was usually determined by previous mortgaging behavior. That meant a neighborhood's nine-quarter cash-flow boost was largely determined by the proportion of adjustable-rate mortgages in 2008Q3, combined with the timing of previous mortgaging activity of those on fixed rates.

The second major concern is that certain types of households selected into fixed and adjustable-rate mortgages between 2005 and 2008. If more financially secure households opted for an adjustable-rate mortgage this might lead to biased estimates if these households had a lower marginal propensity to consume.[25] Table 1 presents some mortgagor statistics by the type of mortgage chosen an origination. On the whole, the characteristics are broadly similar, though fixed-rate mortgagors tend to be slightly younger and with slightly lower incomes. Although they take out similar sized loans, fixed-rate mortgagors are slightly more leveraged relative to income and collateral values.

Table 1 does not provide enough evidence that Equation 3 yields unbiased estimates for the employment response to a cash-flow shock. I therefore construct an instrument that strips out selection bias in the choice between fixed and adjustable-rate mortgages at origination.

# 4 Instrumenting for Neighborhood Cash-flow Shocks

The instrument I construct relies on two key ingredients. First, at least part of households' decisions on whether to pick a fixed or adjustable-rate mortgage was governed by the relative initial price of the two types of contract. Second, at least part of the *exact* timing of the

[25] To the extent wealthier households are often better able to tolerate financial risk, this would be consistent with the theoretical findings of Campbell and Cocco (2003). That said, the direction of bias is unclear given the recent work on high marginal propensities of consumption for the *wealthy hand-to-mouth* (e.g., Violante et al. (2014)).

mortgaging decision was determined by factors unrelated to the business cycle. Since the slope of the yield curve moved around between 2005 and 2008, so did the relative price of fixed-rate mortgages, and the fraction of people taking out adjustable-rate mortgages in a given month. I can therefore use the distribution over *when* people got their mortgage in a particular neighborhood to predict the proportion of people on an adjustable-rate contract in the summer of 2008. Moreover, I can use the same distribution to predict how that fraction of people evolved up until the end of 2010 as peoples' fixed-rate contracts expired and they reset onto the SVR. Since first-time buyers and movers might be more affected by local economic conditions, I restrict my attention to remortgagors.[26] I can then use the neighborhood-level cash-flow shock associated with this predicted adjustable-rate-share evolution to instrument for the actual cash-flow shock the neighborhood received.

## 4.1 Mortgage Choice

Mortgages are poorly understood by households and each mortgage contract has a vast number of non-price terms and options.[27] But the choice between a fixed and adjustable rate is much less important in the UK than in other parts of the world because the length of most fixed-rate contracts is only a couple of years. Consequently, during the Great Moderation, when interest rate volatility was modest, the lifetime cost of choosing an adjustable-rate contract and timing it poorly was on the order of only a few thousand pounds (or, a couple of percentage points of house value). This stands in stark contrast to the US market where the mortgage choice was often between a 30-year fixed rate with the option to refinance and an adjustable-rate mortgage with a tempting teaser rate.

The top panel of Figure 5 shows how much variation there was in the origination of fixed and adjustable-rate mortgages in the five years before the Crisis. At the start of 2005, for

[26] But results are similar if I run the same exercise on all 5m mortgagors.

[27] Agarwal et al. (2015) shows people struggle to calculate the present value of fees compared to additional percentage points on the underlying interest rate, for example.

example, two thirds of new mortgages were issued with an adjustable interest rate. Nine months later that proportion had fallen to around a third. I define the fixed-rate premium (FRP) as the spread between the benchmark two-year 75% LTV fixed-rate mortgage and the two-year 75% LTV adjustable-rate mortgage. The UK mortgage market is competitive and there is surprisingly little variation across lenders in the two benchmark rates they offer over time. They also had very little geographical heterogeneity in their lending activities.

[Figure 5 about here.]

The bottom panel of Figure 5 suggests there was a relationship between the FRP and the likelihood of taking an adjustable-rate mortgage. Coincident with the fall in adjustable-rate mortgage issuance during 2005, the premium associated with the standard fixed-rate mortgage fell by over 50bp. More generally, when the fixed-rate mortgage was more expensive, people were more likely to choose an adjustable-rate contract. The FRP partially captures the market expectation of the future path of UK interest rates and an upward sloping yield curve was associated with people taking out more adjustable-rate mortgages. Before mid 2008, the correlation between the slope of the yield curve and the FRP was 0.77. Figure 5 therefore suggests that time-varying macro factors played a significant role in determining the types of mortgage people picked.

This mechanism is consistent with evidence from Badarinza et al. (2017) that shows people pay more attention to the headline initial rate than whether the overall cost of the mortgage is good value relative to their expectations about the path of policy rates. Many people struggle to understand the mechanics of mortgage finance and the Bank of England's *Public Attitudes to Inflation* survey shows that people do not consider the market curve when deciding how interest rates might move over the next few quarters.[28] Even if households understood how to interpret market prices, it is plausible that many (implicitly) discounted future mortgage payments because they thought their income would increase or

[28]See `https://www.bankofengland.co.uk/inflation-attitudes-survey/2010/august-2010`. Evidence presented in Agarwal and Mazumder (2013) suggests low mathematical ability is associated with poor financial decision making.

higher collateral values would ease the burden of future refinancing.[29] In either case, I can exploit the explanatory power of the yield curve slope in determining mortgage choices as long as mortgagors based at least part of their decision on whether to take out a fixed or adjustable-rate mortgage on the relative attractiveness of the initial interest rate.

Table 2 provides further evidence that decisions were often driven by the slope of the yield curve by using the population of remortgagors. The top panel shows the expected distribution of mortgaging choices under the null hypothesis that the probability of choosing a fixed-rate mortgage was equal to the sample average and independent across time. The bottom panel shows the observed behavior of remortgagors. It shows that over 37% of households that remortgaged between 2005 and 2008 moved onto the opposite interest-rate contract, only 10pp lower than expected under the null hypothesis that the characteristics of fixed and adjustable-rate mortgagors are identical. Not only do a surprisingly large share of households flip mortgage type but the switch is relatively symmetric, which is evidence against life-cycle drivers of the choice of interest-rate type.[30] This supports the claim that many households chose their mortgage type based on marginal factors such as the initial cost rather than fixed and adjustable-rate mortgages being completely segmented markets.

## 4.2 Predicted Cash-flow Shock Construction

I construct a neighborhood-level cash-flow shock that is primarily based on *when* people in that neighborhood took out their mortgages. It therefore combines exogenous variation in the slope of the yield curve with the natural variation of when people took out mortgages in the neighborhood two years before Bank Rate fell. As before, this is divided by the total number of mortgagors in the neighborhood to give a per-household cumulative sterling amount. This predicted cash-flow shock is used to instrument for the actual cash-flow shock

[29] See Cloyne et al. (2019) for evidence in the UK.

[30] For example, it is not the case that younger families always tend to initially get fixed-rate mortgage before switching to an adjustable-rate mortgage later on.

that neighborhoods received.

In order to calculate the neighborhood-level cash-flow shock for Equation 2, I model the quarterly payments of each of the 5m mortgages in 2008Q3. This requires taking estimates of the the loan amount, loan maturity and time remaining on the fixation period and projecting them forward for the following nine quarters. The cumulative difference between the mortgage payments in this modeling exercise and the counterfactual scenario where Bank Rate had remained constant is the modeled cash-flow shock.

The first step in constructing the instrument is to create an expected cash-flow shock for each household based on when they remortgaged. This involves using fitted values from a binary OLS regression of the likelihood of being on an adjustable-rate mortgage (in each quarter between 2008Q3 and 2010Q4) regressed on a dummy for the month of origination (for the 39 months between April 2005 to June 2008). I estimate analogous fitted values for the mortgage term and interest rate at origination using the same monthly dummies. These specifications are shown in Equations 4 to 6 below.

$$Adj_n^t = \alpha + \tau_m + \varepsilon_n \quad \forall\, m \in (2005M4, 2008M6), \quad \forall\, t \in (2008Q3, 2010Q4) \tag{4}$$

$$Term_n = \alpha + \tau_m + \varepsilon_n \quad \forall\, m \in (2005M4, 2008M6) \tag{5}$$

$$Rate_n = \alpha + \tau_m + \varepsilon_n \quad \forall\, m \in (2005M4, 2008M6) \tag{6}$$

The coefficients for these equations are reported in Table 3 where the row is the month of origination and the column is the probability of being on an adjustable rate in that quarter. Moving left to right, the values are weakly increasing as more fixed-rate mortgages reset to the SVR. On the whole, moving top to bottom, the values fall as the proportion of households passed their initial period decreases. But the fall is not monotonic, because the proportion of newly-originated adjustable-rate mortgages varied with the yield curve slope. Almost all coefficients are signification at the 0.1% level. By combining the fitted interest rate and

term with the likely payment evolution for each household, I then estimate the household cash-flow shock for each, for the case where they were on an adjustable-rate or fixed rate at that time. This is shown in Equation 7.

$$C^t_{n,v} = f(p^t_{n,v}, \widehat{Rate}_n, \widehat{Term}_n) \quad \forall t \in (2008Q3, 2010Q4), \ \ \forall v \in \{Adjustable, Fixed\} \tag{7}$$

The next step requires calculating the mean expected cash-flow shock by neighborhood and month of origination, shown in Equation 8. This is done by weighting the household cash-flow shocks estimated in Equation 7 by the binary probabilities in Table 3, summing across time and then averaging across households. This yields a 39 by 1 vector for each neighborhood.

$$\overline{\Delta C}^m_i = \frac{1}{N^m_i} \sum_{n=1}^{N^m_i} \sum_{t=2008Q3}^{T=2010Q4} \widehat{Adj}^t_n \times C^t_{n,Adj} + (1 - \widehat{Adj}^t_n) \times C^t_{n,Fix} \tag{8}$$

To get the predicted cash-flow shock for each neighborhood, this vector needs to be combined with a (39 by 1) weighting vector, $\theta^m_i$, which is is shown in Equation 9. $\theta^m_i$ captures the temporal distribution of when mortgages in a particular neighborhood were originated. Although some variation in the predicted cash-flow shock across neighbourhoods comes from $\overline{\Delta C}^m_i$, the bulk come from $\theta^m_i$ because this determines when fixed-rate mortgagors reset to adjustable rates.

$$\overline{\Delta C}_i = \sum_{m=1}^{39} \theta^m_i \overline{\Delta C}^m_i, \ \ where \sum \theta^m_i = 1 \tag{9}$$

The simplest course would be to weight the cash-flow shock vector by the distribution of the number of mortgages issued in each month for that neighborhood.[31] But in the main specification I weight the mean predicted cash-flow shocks by the time distribution

[31]Figure A1 in the Appendix illustrates the variation across months-of-origination in the PSD data. As described below, any residual variation from the cash-flow shock vector is dealt with in the main specification by using regional fixed effects and adding house price controls.

of mortgage transactions from Land Registry data two years prior. The distribution of transactions two years prior is correlated with the contemporaneous timing distribution because so many people were on contracts with a two year initial term. Short fixation periods and large spreads to SVR-reset rates meant that people had a strong incentive to refinance when their mortgage deal expired before the Crisis. Over half of the mortgages in the fall of 2008 were remortgages. At the same time, hefty early repayment fees on the order of percentage points of loan-value-outstanding limited the attractiveness of applying for a remortgage too early. Using matched remortgages contained within my stock, I estimate that around 40% of people refinanced within a few weeks of the end of their contractual maturity and around three quarters within a few months (see Figure 6, which is is similar to Figure A.1 in Best et al. (2015)). Using this alternative weighting distribution helps satisfy the exclusion restriction because contemporaneous mortgaging choices are more likely to be correlated with local economic conditions.

[Figure 6 about here.]

Figure 7 shows the relationship between the predicted cash-flow shock and the actual cash-flow shock per mortgagor in each neighborhood.[32] Figure 8 shows the employment trends in the locally non-tradable sector when the wards are categorized as above and below the median predicted cash-flow shock. It shows that before the Crisis employment trends were similar but a gap starts opening up in the year following the fall in Bank Rate.

[Figure 7 about here.]

[Figure 8 about here.]

[32]Table A5 shows some correlations between the predicted cash-flow shock and neighborhood characteristics.

# 5 Results

## 5.1 Summary Statistics

Variation in the choice of interest type and when people got their mortgage diffracted the direct effect of monetary policy into a heterogeneous cash-flow shock across mortgagors. Figure 9 shows the distribution of that cash-flow shock across mortgagors on both fixed and adjustable-rate contracts as of the middle of 2008. The left-hand panel shows that cash-flow shocks for those on fixed-rate mortgages were clustered closer to zero; around a third of these households received no cash-flow shock at all. Nevertheless, because the average length of the fixed period was a little over two years, many fixed-rate households were able to roll onto the SVR at some point and gain some direct benefit of the monetary stimulus before the end of 2010. The mean (median) nine-quarter cash-flow shock for these mortgagors was around £2,900 (£1,700), which was equivalent to around 2.6% (2.0%) of their gross income over this period.

[Figure 9 about here.]

Those on adjustable-rate contracts received a mean (median) cash-flow shock of around £8,000 (£5,400), equivalent to around 5.5% (5.0%) of their gross income. This is an economically significant number; only slightly below the household saving rate during the Great Moderation. For many, it was equivalent to around 8% of post-tax income and perhaps closer to 30% of annual discretionary income (after subtracting food, travel, etc).[33] The spatial distribution of fixed and adjustable-rate mortgagors at different points in time led to heterogeneity in the average cash-flow shock for each neighborhood. Figure 10 shows the predicted cash-flow shock for each neighborhood when the timing of each mortgaging decision is the sole determinant of the time left on a fixed rate from 2008Q3, described above. This is used to instrument for the actual cash-flow shock in the main regressions.

[33]See ONS data series NRJS. This is also consistent with survey evidence. For example, households saved around 8% of income in 2013 (Bunn et al. (2013)). Median household disposable income per head in 2010 was around £16,000.

[Figure 10 about here.]

Table 4 presents the summary statistics associated with the main set of regressions, split by wards above and below the median predicted cash-flow shock. It shows that the main sample consists of almost 8,000 contiguous neighborhoods, each containing an average of just over 500 mortgages. Around a third of households were on an adjustable-rate contract at origination. The average neighborhood mortgagor cash-flow shock was £4,500. The mean neighborhood employed around 470 people in the locally non-tradable sector, and this constituted just over a fifth of overall the private-sector employment. The average neighborhood experienced a 3% reduction in locally non-tradable employment between 2007 and 2010.

## 5.2 Local Employment Cash-flow Effect

Table 5 presents the main results of estimating $\beta$ in Equation 3 using the definitions in Equations 1 and 2. The first column shows the first stage of the IV estimation using the predicted cash-flow shock as an instrument for the actual neighborhood cash-flow shock. The statistically significant coefficient in the second row and high Kleibergen-Paap F statistic show that the instrument has high relevance.[34] The second column uses a standard OLS approach and suggests that a cash-flow shock equivalent to £1,000 per mortgagor was associated with an increase in locally non-tradable employment growth of 0.34pp and is statistically significant at the 0.1 percent level when standard errors are clustered by the 343 local authorities. The third column shows the main IV estimates are little different to the OLS specification.

One of the main contributions of this work is to quantify the employment effect of cash-flow shocks via local spending. There is currently very limited evidence on how large this effect is, though Di Maggio et al. (2017) estimate that every 10pp increase in the zip-code share of adjustable-rate mortgages increases the overall employment growth rate by 0.29pp.

[34]The IV estimates only have around 8,000 neighborhoods because Land Registry data, used to for the lagged distribution of transactions, is only available in England and Wales.

Column 4 runs a regression in a similar style where the independent variable is the proportion of adjustable-rate mortgagors in 2008Q3. This estimate suggests that every 10pp increase in adjustable-rate mortgages increases locally non-tradable employment by 1.76pp. Since locally non-tradable employment represents around a fifth of overall private-sector employment, that yields an estimate for total employment growth of around 0.35pp.

Another way of exploring the plausibility of my estimates is to consider what they imply for the cash-flow shock required to add, or sustain, one job. For lower mortgage payments to have directly boosted employment, people must have spent at part of the windfall in the local economy. There is a large body of evidence that provides plausible ranges for the typical marginal propensities to consume for mortgagors. Survey evidence from the US (Fuster et al. (2018)), the UK (Bunn et al. (2018b) and the Netherlands (Christelis et al. (2019)) points to a typical marginal propensity to consume out of a positive income shock of between 0.1 and 0.2.[35] There is, however, currently little evidence regarding how consumption decisions are split across spending categories, or how much people might spend on locally-provided goods and services. In Appendix 10.4 I use UK expenditure surveys and tax rebate shocks to provide some supporting evidence for how windfalls are spent on different parts of the consumption basket.

Each neighborhood has around 500 mortgagors so a £1,000 cash-flow shock leads to an aggregate boost of around £500,000. Each neighborhood employs around 470 people in the locally non-tradable sector, which means my estimates suggest this cash-flow shock should increase employment by around 1.4 people. That implies each job requires a cash-flow boost of around £350,000.[36] Using 0.2 as the marginal propensity to consume yields a total spend of around £70,000. Finally, between 2006 and 2017 the average mortgagor spent around half

[35]Studies that look at financial returns tend to produce slightly lower estimates, especially for those towards the top of the income distribution (Di Maggio et al. (2018)). But lottery evidence from Norway is consistent with much larger marginal propensities, perhaps even close to 1 after enough time for the smallest unexpected windfalls (Fagereng et al. (2019)).

[36]Verner and Gyongyosi (2018) find that an increased debt burden of around £150,000 (in 2008 dollars) destroys one job. It is hard to directly compare these flow and stock estimates, but on the face of it they seem broadly similar.

their total consumption basket on locally non-tradable goods and services.[37] The average annual wage of a locally non-tradable worker is around £15,000, though the marginal cost of employing a worker is likely a little higher.[38] Put together, these results are therefore of the right order of magnitude given available estimates and data.

## 5.3 Robustness

I perform a number of robustness checks to test the empirical specification and rule out competing channels in Table 6. In the first column I test whether using the contemporaneous-timing-distribution IV specification alters the main message. In fact, while the two year-lag specification is helpful in terms of bolstering instrument exogeneity, it is of little importance for the point estimates. It is also worth noting why this predicted cash-flow shock only affects mortgagors and not the owners of the locally non-tradable establishments. First, small businesses predominantly took variable-rate bank loans before the Crisis and only a few larger businesses were able to access fixed-rate capital-market instruments. In 2007, 99.9% of firms in the locally non-tradable sector employed fewer than 1,300 people and accounted for over half of all locally non-tradable employment.[39] Second, more than 60% of company directors live in a different region to where their establishments are located.[40] So it seems unlikely that the results are driven by directors taking the windfall from their own mortgage to support employment.

Another concern is that the neighborhoods that received the largest cash-flow shocks are in some ways different, perhaps because of their employment structure. In the second column I add in controls for the manufacturing employment share and GVA per capita for each neighborhood. This measure is constructed by taking the regional-average GVA per

[37] Data from the Living Costs and Food Survey. Locally non-tradable spending is defined as spending on restaurants, recreation, food, and miscellaneous goods and services.

[38] See Table A4 in the Appendix.

[39] While Gürkaynak et al. (2019) exploit variation in the type of debt businesses took out to answer a similar question, stock-exchange listed businesses are a small fraction of overall employment.

[40] See Bahaj et al. (2017) for details.

capita in 2007 for each sector and weighting it by the neighborhood's sectoral employment distribution. The estimate for column 2 is close to the main specification.

Some neighborhoods might have been hit by shocks of different magnitudes in the Great Recession. Figure 8 provides some comfort that neighborhoods above and below the median predicted cash-flow shock did not behave very differently in the years before 2008. In column 3 I add in the neighborhood GVA change between 2007 and 2010 using the same methodology as above to control for the size of the economic shock neighborhoods faced. In addition I add a control for the change in employment (excluding locally non-tradable employment) between 2007 and 2010 and it does little to the central estimates.

Another plausible channel through which local non-tradable employment could be supported is via property prices. The first concern is that neighborhoods with higher house prices received larger cash-flow shocks. While this is true to a limited extent, property prices are spatially correlated so much of this level effect is soaked up in the regional fixed effect.[41] In addition, I add in the local authority house price index in the fourth column to control for prices at a more granular level. The second concern is that house price falls led to wealth or collateral effects that caused some of the variation in spending. I therefore add in the change in local-authority house prices between 2008Q3 and the end of 2010 in column 4, with little impact on the central estimate.[42] London had quite unique property price dynamics and also accounts for quite a bit of the variation in cash-flow shock and employment. The fifth column shows that dropping all Greater London wards entirely reduces the precision of the estimates.

It is also worth probing the timing of the specification I have chosen. Figure 11 shows an event study of the main IV regression coefficients for alternative three-year windows, starting from 2001-2004. The left-hand panel shows that the regressions on the 2008 mortgage

[41] For example, the average house price for a first-time buyer in the first six months of 2008 was £266,000 in London compared to £118,000 in the North of England.

[42] Residential property price changes are likely to be correlated with local commercial property prices too, though most small firms do no own property

stock provide estimates close to zero before 2009. After rising to around 0.4pp in 2011, the estimates fall back to zero after the cash-flow shock had fully passed through to all mortgagors by 2012. The choice of the 2007 to 2010 window is a trade-off. On the one hand I want to give establishments time to respond to the heterogeneous spending patterns. On the other, later estimates are more likely to be compromised by second-round effects of the cash-flow shock (such as spending response of those whose employment status had been affected by the initial cash-flow shock) and the wider effects of monetary policy. The right-hand panel shows the analogous estimates for manufacturing employment, which are volatile but close to zero for most of the post-2008 sample. The manufacturing comparison also helps to rule out other channels such as labor-supply effects or director windfalls.

[Figure 11 about here.]

Finally, Table A6 in the Appendix shows some further robustness checks around the regression specifications. The first column shows that the precision of the estimates is barely affected when the standard errors are clustered by the 10 regions rather than the 343 local authorities. The second column shows that the central estimates fall by half when the regressions are equally weighted across wards. Like in Verner and Gyongyosi (2018), this is likely due to the fact that the effects are stronger in larger and more densely populated areas, where more of the windfall is spent locally. This is another reason why the coefficient excluding London is lower in Table 6. The third column is a regression of the unweighted linear change in employment. Using this for the plausibility calculations suggests a cash-flow shock of around £150,000 is required to save one job, and is a surely a lower bound. To ensure the main results are not driven by outliers, I drop the wards with largest cash-flow shocks and employment in the final two columns. Although the estimates are less precise, they remain of the right magnitude.

# 6 Exploring Employment Responses

The main results provide supporting evidence to the hypothesis that neighborhoods receiving larger cash-flow shocks spent more money locally, and this supported employment in the locally non-tradable sector. But so far the analysis reveals little about how firms actually responded or where this effect was felt the greatest. In this section I develop my ward-level analysis and exploit the establishment-level data to dig deeper into these questions.

## 6.1 Employment at the Neighborhood Level

The first three columns of Table 7 examine the ward-level margin of adjustment for locally non-tradable employment. The first column suggests that a £1,000 cash-flow shock per mortgagor increased the probability of an establishment being born in 2010 by around 6 basis points. More significantly in an economic and statistical sense, the second column suggests that the same cash-flow shock reduced the probability of an establishment dying by 10 basis points. To put these results in context, moving from the $10^{th}$ to the $90^{th}$ percentile cash-flow shock increased (decreased) the probability of an establishment being born (dying) by 40bp (24bp), given a mean birth (death) rate of 25% (31%). The third column clarifies the relative margins of adjustment by summing employment for establishments that existed in both 2007 and 2010 and performing the baseline regression. As a whole, the results suggest that just under two thirds of the overall employment adjustment happened through establishments hiring more workers (or firing fewer workers). Of the remaining third, around two thirds of that effect was accounted for by establishments not shutting down when they otherwise would have.

The last four columns of Table 7 go back to allowing for both the extensive and intensive margin but only consider certain types of establishments. The fourth column considers establishments belonging to a medium-size chain (defined here as an enterprise with between 10 and 100 establishments). The estimated coefficient is around three times as large as in

the main results. This provides further comfort that the cash-flow effect is not confounded by other channels, which might be more likely to affect enterprises with a small number of employees. For employment in these medium-sized chains, the large coefficient likely reflects easier human resource management that comes with a larger number of employees across different locations. The flip side is that solo-establishment enterprises adjusted employment less in response to neighborhood cash-flow shocks.

The final three columns split employment into the three broad sectors that make up the definition of locally non-tradable employment. The results suggests that the employment effect of local spending is substantially larger for establishments in the auto or the restaurant sector. In fact, I find that the employment effect in the retail sector is essentially zero. This could reflect characteristics of these sectors on both the demand and supply side. On the demand side, discretionary spending at restaurants is very likely to be boosted by a windfall. At the same time, car purchase or repair is often expensive so cash-flow boosts could catalyze a transaction that was previously delayed. The majority of employment in the retail sector is in shops that sell food and other essentials, so it is perhaps unsurprising that employment in this sector is not sensitive to an increase in disposable income. Moving from types of establishments to types of workers, in Appendix 10.5 I show that the employment effect was roughly equally shared between full-time and part-time workers using survey data.

## 6.2 Employment at the Establishment Level

Table 7 shows analogous information to Table 8 at the establishment level, where the pooled IV regressions are weighted by establishment size and standard errors are double clustered at the enterprise and local-authority level. Table 9 shows the results of an IV probit regression where establishments in 2007 are matched with those in 2010. To aid interpretation, only the marginal probabilities of birth and death are reported at the $10^{th}$ and $90^{th}$ percentile cash-flow shocks, in the upper and lower panels, respectively.

The point estimate in the first column of Table 8 matches the results at the neighborhood level when all 250,000 surviving establishments are included. The second column provides evidence that around a third of the employment effect for chain establishments is via the intensive margin. Interestingly, a much greater proportion of the employment effect in the auto sector comes about through hiring workers in the third column. That is also true relative to the restaurant sector, though its coefficient is much less precisely estimated in the fourth column. There is no intensive-margin effect for the retail sector. The final four columns show the intensive margin for establishments of different size, roughly split into quartiles. Counterintuitively, the intensive-margin employment effect is actually decreasing in establishment size. This mechanism might be similar to the delayed-purchase channel: consider a turnover boost finally giving an establishment the opportunity to hire an additional worker, which naturally leads to larger percentage changes for small base numbers.

Table 8 completes the establishment-level picture with the extensive margin. When considering all establishments, moving from the $10^{th}$ to the $90^{th}$ percentile cash-flow shock increases the probability of an establishment being born by 0.7pp and decreases the probability of dying by 0.1pp. For chain establishments in the second column, the probability of death actually increases in the size of the windfall, as it does for the auto sector and larger establishments in columns 7 to 9. In the restaurant sector, the equivalent cash-flow shock reduces the probability of death by over 1.5pp, which appears to account for over half of the overall employment effect.

Some caution is needed when interpreting these results since establishment-level regressions are noisy and the intensive and extensive margins are hard to compare directly, since one is about workers and the other is about sets of workers. But these results paint a picture of heterogeneity in the employment cash-flow effect across margins, sectors and establishment sizes. The central estimate for locally non-tradable employment belies the fact that over 60% of locally non-tradable employees work in retail units, which have a very low sensi-

tivity to the cash-flow effect. Since the restaurant sector employed almost a third of locally non-tradable workers, it was these establishments that drove the direct employment response during the Great Recession.

# 7 Conclusion

I find that the monetary easing by the Bank of England in the fall of 2008 had a significant and immediate cash-flow impact on people with an adjustable-rate mortgages. In areas where the overall cash-flow shock was especially large, it supported spending, including consumption for locally provided goods and services, thereby supporting employment in these sectors. Although monetary policy works through multiple channels, I find the cash-flow channel via locally non-tradable employment is sizable at the establishment level and leads to heterogeneous effects across sectors.

The diffraction of the cash-flow shock through regional mortgage and labor market structures also led to a heterogeneous spatial impact of monetary policy through the cash-flow channel. Neighborhoods that happened to contain a large proportion of people on adjustable-rate mortgages and employed a large fraction of their labor force in the locally non-tradable sector benefited the most from the first-round effects of accommodative monetary policy. My results suggest, for a neighborhood in the top quartile in terms of locally non-tradable employment share, a top-quartile cash-flow shock led to an increase in overall employment growth of around 0.5pp relative to a bottom-quartile cash-flow shock.[43]

One consequence of this work is that monetary policy can lead to heterogeneous employment effects across space, as well as time. To the extent there are significant differences in the mortgage and labor markets across countries, this paper also sheds light on how the transmission of monetary policy might vary across the globe. But my work also has implications for

[43]Spatial implications are consistent with the identification used in this paper. Applying cross-sectional identification to an aggregate effect requires some strong assumptions, many of which are laid out in Nakamura and Steinsson (2018).

the traction of monetary policy over time. Since policy rates reached their Great-Recession nadir in 2009, many countries have seen an increase in the demand for fixed-rate contracts, as people have tried their best to lock in low rates for an extended period of time. This is likely to change the monetary transmission mechanism in important ways for policymakers going forward.

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# 8 Tables

**TABLE 1.** Mortgagor Statistics in July 2008

| Statistic | N | Mean | St. Dev. | $25^{th}$ pctl | Median | $75^{th}$ pctl |
|---|---|---|---|---|---|---|
| **Adjustable-rate** | | | | | | |
| Age | 1,671,530 | 41.17 | 10.27 | 34 | 40 | 48 |
| Single income | 830,384 | 57,624 | 233,487 | 25,000 | 36,000 | 57,500 |
| Joint income | 841,146 | 68,228 | 131,881 | 36,000 | 50,000 | 72,911 |
| Loan size | 1,671,530 | 141,830 | 137,097 | 70,000 | 110,497 | 170,599 |
| House price | 1,671,530 | 254,941 | 241,949 | 140,000 | 200,000 | 293,000 |
| LTV | 1,671,530 | 59.09 | 24.61 | 39.30 | 60.70 | 80.30 |
| LTI | 1,671,530 | 2.66 | 1.19 | 1.86 | 2.64 | 3.36 |
| Initial period | 1,671,530 | 2.21 | 1.21 | 2 | 2 | 2 |
| **Fixed-rate** | | | | | | |
| Age | 3,331,885 | 37.72 | 10.08 | 30 | 37 | 44 |
| Single income | 1,557,485 | 41,528 | 110,587 | 22,500 | 30,500 | 45,000 |
| Joint income | 1,774,398 | 53,578 | 90,507 | 33,520 | 43,657 | 59,177 |
| Loan size | 3,331,885 | 128,298 | 95,722 | 75,000 | 110,000 | 155,726 |
| House price | 3,331,885 | 202,015 | 170,507 | 122,000 | 167,000 | 235,000 |
| LTV | 3,331,885 | 67.17 | 23.54 | 50.18 | 72.29 | 87.88 |
| LTI | 3,331,885 | 2.94 | 1.10 | 2.27 | 2.96 | 3.60 |
| Initial period | 3,331,885 | 2.48 | 1.36 | 2 | 2 | 2 |

This table shows the observable characteristics of mortgages at the end of 2008Q2. Interest-rate types are those designated at origination. Initial periods refer to the length of the contract before the interest rate resets to the Standard Variable Rate.

**TABLE 2.** Evidence for Quasi-Random Mortgage Selection

**Expected | no intertemporal relationship, percent**

| | **Second mortgage** | |
|---|---|---|
| **First mortgage** | Adjustable | Fixed |
| Adjustable | 13.7 | 23.3 |
| Fixed | 23.3 | 39.7 |

*Note:* Pr*(Fixed) = 63%*

**Observed transition matrix, percent**

| | **Second mortgage** | |
|---|---|---|
| **First mortgage** | Adjustable | Fixed |
| Adjustable | 18.5 | 16.8 |
| Fixed | 20.1 | 44.6 |

There were 763,276 people who remortgaged once between 2005 and 2008 and, in total, 63% of the mortgages were fixed-rate contracts. If the probability of choosing a fixed-rate contract was independent across time we would expect to see the distribution in the top panel. For example, the probability of choosing a fixed-rate contract twice is $0.63 \times 0.63 = 39.7\%$. The observed distribution is shown in the bottom panel.

**TABLE 3.** Fitted Values for Instrument Construction

| Month of origination | Probability of being on a variable rate in this quarter | | | | | | | | | | | | Overall |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2008Q3 | 2008Q4 | 2009Q1 | 2009Q2 | 2009Q3 | 2009Q4 | 2010Q1 | 2010Q2 | 2010Q3 | 2010Q4 | Mortgage term | Initial Rate | proportion(%) |
| 2005 M4 | 0.82 | 0.82 | 0.82 | 0.82 | 0.82 | 0.82 | 0.82 | 0.82 | 0.96 | 0.96 | 18.24 | 5.15 | 1.33 |
| 2005 M5 | 0.81 | 0.81 | 0.81 | 0.81 | 0.81 | 0.81 | 0.81 | 0.81 | 0.96 | 0.96 | 18.38 | 5.16 | 1.41 |
| 2005 M6 | 0.80 | 0.80 | 0.80 | 0.80 | 0.80 | 0.80 | 0.80 | 0.80 | 0.96 | 0.96 | 18.55 | 5.16 | 1.65 |
| 2005 M7 | 0.57 | 0.76 | 0.76 | 0.76 | 0.75 | 0.76 | 0.76 | 0.76 | 0.77 | 0.96 | 18.62 | 5.14 | 1.71 |
| 2005 M8 | 0.51 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.74 | 0.95 | 18.61 | 5.07 | 1.88 |
| 2005 M9 | 0.45 | 0.70 | 0.70 | 0.70 | 0.70 | 0.71 | 0.71 | 0.71 | 0.72 | 0.94 | 18.65 | 5.03 | 2.00 |
| 2005 M10 | 0.46 | 0.46 | 0.72 | 0.72 | 0.72 | 0.72 | 0.73 | 0.73 | 0.73 | 0.73 | 18.74 | 4.99 | 1.97 |
| 2005 M11 | 0.47 | 0.47 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.74 | 0.74 | 18.72 | 4.98 | 2.10 |
| 2005 M12 | 0.47 | 0.47 | 0.73 | 0.73 | 0.73 | 0.73 | 0.74 | 0.74 | 0.74 | 0.74 | 18.84 | 5.00 | 2.00 |
| 2006 M1 | 0.52 | 0.52 | 0.52 | 0.76 | 0.76 | 0.76 | 0.76 | 0.77 | 0.77 | 0.77 | 18.74 | 5.02 | 1.76 |
| 2006 M2 | 0.55 | 0.55 | 0.55 | 0.78 | 0.77 | 0.77 | 0.77 | 0.78 | 0.79 | 0.79 | 18.90 | 5.02 | 1.81 |
| 2006 M3 | 0.57 | 0.57 | 0.57 | 0.78 | 0.77 | 0.77 | 0.77 | 0.78 | 0.79 | 0.79 | 18.79 | 5.02 | 2.30 |
| 2006 M4 | 0.56 | 0.56 | 0.56 | 0.56 | 0.76 | 0.76 | 0.76 | 0.76 | 0.77 | 0.77 | 18.94 | 5.01 | 2.14 |
| 2006 M5 | 0.56 | 0.56 | 0.56 | 0.56 | 0.75 | 0.75 | 0.75 | 0.75 | 0.77 | 0.77 | 19.12 | 5.01 | 2.69 |
| 2006 M6 | 0.58 | 0.58 | 0.58 | 0.58 | 0.76 | 0.76 | 0.76 | 0.76 | 0.78 | 0.78 | 19.26 | 5.02 | 3.01 |
| 2006 M7 | 0.49 | 0.69 | 0.69 | 0.69 | 0.68 | 0.81 | 0.81 | 0.81 | 0.82 | 0.83 | 19.31 | 5.04 | 3.00 |
| 2006 M8 | 0.52 | 0.71 | 0.71 | 0.71 | 0.71 | 0.82 | 0.82 | 0.82 | 0.83 | 0.84 | 19.42 | 5.10 | 3.27 |
| 2006 M9 | 0.50 | 0.71 | 0.71 | 0.71 | 0.71 | 0.82 | 0.82 | 0.82 | 0.83 | 0.84 | 19.39 | 5.14 | 2.96 |
| 2006 M10 | 0.49 | 0.49 | 0.80 | 0.80 | 0.79 | 0.79 | 0.87 | 0.87 | 0.88 | 0.88 | 19.46 | 5.15 | 3.21 |
| 2006 M11 | 0.47 | 0.47 | 0.80 | 0.80 | 0.79 | 0.79 | 0.87 | 0.87 | 0.88 | 0.88 | 19.31 | 5.17 | 3.52 |
| 2006 M12 | 0.45 | 0.45 | 0.79 | 0.79 | 0.78 | 0.78 | 0.86 | 0.86 | 0.87 | 0.87 | 19.48 | 5.19 | 3.01 |
| 2007 M1 | 0.37 | 0.37 | 0.37 | 0.79 | 0.78 | 0.78 | 0.78 | 0.86 | 0.87 | 0.87 | 19.42 | 5.45 | 2.78 |
| 2007 M2 | 0.30 | 0.30 | 0.30 | 0.75 | 0.74 | 0.74 | 0.74 | 0.84 | 0.85 | 0.85 | 19.32 | 5.52 | 2.60 |
| 2007 M3 | 0.29 | 0.29 | 0.29 | 0.75 | 0.74 | 0.74 | 0.74 | 0.83 | 0.84 | 0.84 | 19.37 | 5.57 | 3.25 |
| 2007 M4 | 0.28 | 0.28 | 0.28 | 0.28 | 0.70 | 0.70 | 0.70 | 0.70 | 0.82 | 0.82 | 19.63 | 5.61 | 2.94 |
| 2007 M5 | 0.30 | 0.30 | 0.30 | 0.30 | 0.69 | 0.69 | 0.69 | 0.69 | 0.81 | 0.81 | 19.49 | 5.68 | 3.31 |
| 2007 M6 | 0.27 | 0.27 | 0.27 | 0.27 | 0.69 | 0.69 | 0.69 | 0.69 | 0.82 | 0.82 | 19.50 | 5.72 | 3.45 |
| 2007 M7 | 0.26 | 0.28 | 0.28 | 0.28 | 0.27 | 0.72 | 0.72 | 0.72 | 0.72 | 0.82 | 19.65 | 5.79 | 3.48 |
| 2007 M8 | 0.31 | 0.33 | 0.33 | 0.33 | 0.32 | 0.72 | 0.72 | 0.72 | 0.73 | 0.83 | 19.71 | 5.88 | 3.49 |
| 2007 M9 | 0.35 | 0.37 | 0.37 | 0.37 | 0.36 | 0.75 | 0.75 | 0.75 | 0.75 | 0.85 | 19.92 | 5.93 | 3.06 |
| 2007 M10 | 0.37 | 0.37 | 0.40 | 0.40 | 0.39 | 0.39 | 0.84 | 0.84 | 0.85 | 0.85 | 19.80 | 5.93 | 3.28 |
| 2007 M11 | 0.40 | 0.40 | 0.43 | 0.43 | 0.42 | 0.42 | 0.85 | 0.85 | 0.86 | 0.86 | 19.46 | 5.94 | 2.93 |
| 2007 M12 | 0.43 | 0.43 | 0.45 | 0.45 | 0.45 | 0.45 | 0.86 | 0.86 | 0.87 | 0.87 | 19.44 | 5.92 | 2.23 |
| 2008 M1 | 0.48 | 0.48 | 0.48 | 0.50 | 0.49 | 0.49 | 0.49 | 0.84 | 0.85 | 0.85 | 19.69 | 5.86 | 2.48 |
| 2008 M2 | 0.53 | 0.53 | 0.53 | 0.54 | 0.54 | 0.54 | 0.54 | 0.83 | 0.84 | 0.84 | 19.54 | 5.81 | 2.42 |
| 2008 M3 | 0.49 | 0.49 | 0.49 | 0.51 | 0.50 | 0.50 | 0.50 | 0.78 | 0.79 | 0.79 | 19.49 | 5.78 | 2.24 |
| 2008 M4 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.55 | 0.55 | 19.60 | 5.74 | 2.59 |
| 2008 M5 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.47 | 0.47 | 19.76 | 5.76 | 2.42 |
| 2008 M6 | 0.33 | 0.33 | 0.33 | 0.33 | 0.32 | 0.32 | 0.32 | 0.32 | 0.45 | 0.45 | 19.79 | 5.81 | 2.30 |
| $R^2$ | 0.06 | 0.10 | 0.14 | 0.15 | 0.13 | 0.10 | 0.10 | 0.09 | 0.07 | 0.08 | 0.00 | 0.44 | |

This table summarizes the probability that a remortgage originated in the row-month is an adjustable-rate mortgage by the time of the column-quarter for 2.6m remortgages originated between 2005M4 and 2006M6. Moving left to right, the values are weakly increasing as more fixed-rate mortgages reset to the SVR. On the whole, moving top to bottom, the values fall the proportion on mortgages passed their initial period decreases. But the fall is not monotonic, because the proportion of newly originated adjustable-rate mortgages varied with the yield curve slope. Almost all coefficients are signification at the 0.1% level.

**TABLE 4.** Neighborhood Summary Statistics

| Statistic | N | Mean | St. Dev. | $25^{th}$ pctl | Median | $75^{th}$ pctl |
|---|---|---|---|---|---|---|
| **Wards below median fitted cash-flow shock** | | | | | | |
| Actual cash-flow shock, £ | 4,045 | 3,176 | 1,259 | 2,366 | 2,983 | 3,645 |
| Fitted cash-flow shock, £ | 4,045 | 2,749 | 545 | 2,384 | 2,800 | 3,185 |
| Share of flexible-rate mortgages, % | 4,045 | 35.10 | 7.80 | 29.64 | 34.24 | 39.65 |
| Number of mortgaged households | 4,045 | 546.7 | 369.5 | 277 | 458.5 | 746 |
| Population | 4,045 | 5,448 | 3,879 | 2,566 | 4,405 | 7,375 |
| Age | 4,045 | 41.33 | 2.14 | 39.89 | 41.02 | 42.49 |
| LTV | 4,045 | 57.50 | 5.84 | 53.73 | 58.10 | 61.84 |
| LTI | 4,045 | 2.58 | 0.17 | 2.46 | 2.57 | 2.70 |
| House price change, 2010Q1-08Q3, % | 4,045 | −4.77 | 3.45 | −7.08 | −4.81 | −2.39 |
| Share LNT employment, % | 4,045 | 23.43 | 14.04 | 12.61 | 20.94 | 31.41 |
| GVA level, £000 per capita | 4,045 | 49.52 | 14.62 | 42.21 | 47.35 | 53.63 |
| GVA change, 2010Q-2007, % | 4,045 | −3.60 | 4.37 | −6.62 | −3.90 | −0.69 |
| LNT employment 2007 | 4,045 | 469.16 | 910.34 | 83 | 207 | 520 |
| LNT establishments 2007 | 4,045 | 51.21 | 69.19 | 16 | 31 | 61 |
| LNT employment 2010 | 4,045 | 460.09 | 862.02 | 79 | 201 | 512 |
| LNT establishments 2010 | 4,045 | 67.80 | 91.74 | 21 | 41 | 82 |
| Change in LNT empl., 2010-07, % | 4,045 | −3.47 | 31.48 | −17.28 | −3.81 | 9.84 |
| **Wards above median fitted cash-flow shock** | | | | | | |
| Actual cash-flow shock, £ | 4,046 | 7,209 | 3,742 | 4,855 | 6,183 | 8,384 |
| Fitted cash-flow shock, £ | 4,046 | 5,363 | 1,924 | 4,147 | 4,803 | 5,933 |
| Share of flexible-rate mortgages, % | 4,046 | 41.41 | 7.73 | 36.12 | 41.33 | 46.58 |
| Number of mortgaged households | 4,046 | 510.7 | 349.5 | 233 | 422 | 710 |
| Population | 4,046 | 5,233 | 3,517 | 2,521 | 4,186 | 7,288 |
| Age | 4,046 | 42.98 | 2.27 | 41.40 | 42.95 | 44.54 |
| LTV | 4,046 | 53.83 | 5.28 | 50.14 | 53.55 | 57.25 |
| LTI | 4,046 | 2.75 | 0.16 | 2.65 | 2.75 | 2.85 |
| House price change, 2010Q1-08Q3, % | 4,046 | −2.18 | 3.41 | −4.11 | −2.11 | −0.06 |
| Share LNT employment, % | 4,046 | 19.82 | 11.33 | 11.54 | 17.56 | 25.94 |
| GVA level, £000 per capita | 4,046 | 55.92 | 18.03 | 44.68 | 52.27 | 62.37 |
| GVA change, 2010Q-2007, % | 4,046 | −1.74 | 3.59 | −4.03 | −1.67 | 0.57 |
| LNT employment 2007 | 4,046 | 474.69 | 1,122.66 | 102 | 208 | 464.8 |
| LNT establishments 2007 | 4,046 | 52.40 | 79.49 | 18 | 32 | 60 |
| LNT employment 2010 | 4,046 | 467.76 | 1,136.31 | 98 | 205 | 461.8 |
| LNT establishments 2010 | 4,046 | 71.08 | 109.00 | 25 | 43 | 81 |
| Change in LNT empl., 2010-07, % | 4,046 | −2.55 | 30.13 | −16.99 | −2.68 | 12.02 |

This table presents summary statistics for the neighborhood data used in the analysis. The population estimates are constructed using postcode-level census data. House price changes are from the ONS local-authority series. Locally non-tradable (LNT) employment data are derived from the BSD and the neighborhood GVA shocks are constructed using the neighborhood share of employment in each of the 17 main industrial sector categories and regional GVA indices. All other data are constructed from the PSD. Data are for England and Wales only.

**TABLE 5.** Main Neighborhood Regressions

| | Employment growth, pp | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | First Stage | No Instrument | Main Specification | Di Maggio et al (AER 2017) |
| Cash-flow shock | | 0.339*** | 0.333*** | |
| (£000) | | (3.508) | (3.381) | |
| Fitted cash-flow | 1.954*** | | | |
| (£000) | (31.451) | | | |
| Adjustable-rate share | | | | 0.176** |
| (% of mortages) | | | | (3.026) |
| Region fixed effects | Yes | Yes | Yes | Yes |
| Specification | OLS | OLS | IV | OLS |
| Observations | 8,115 | 8,115 | 8,115 | 8,115 |
| $R^2$ | 0.955 | 0.007 | 0.007 | 0.007 |
| F stat | 332.10 | 3.78 | 33.17 | 2.17 |
| *Note:* | | | | *p<0.05; **p<0.01; ***p<0.001 |

Dependent variable is the neighbourhood-level locally non-tradable employment growth between 2007 and 2010. Regressions are weighted by employment and standard errors are clustered at the local-authority level. There are 10 regions and 343 local authorities.

**TABLE 6.** Robustness

| | Employment growth, pp | | | | |
|---|---|---|---|---|---|
| | (1) Contemp. Instr. | (2) Local Controls | (3) Econ. Shock | (4) HP Channel | (5) Exc. London |
| Cash-flow shock | 0.322*** | 0.327*** | 0.328*** | 0.255** | 0.249 |
| (£000) | (3.376) | (3.480) | (3.681) | (2.612) | (1.486) |
| Manufacturing share | | −0.001 | −0.001 | −0.001 | |
| (% of employment) | | (−1.241) | (−1.090) | (1.121) | |
| GVA per capita | | 0.015 | 0.014 | 0.013 | |
| (£000) | | (0.436) | (0.443) | (0.411) | |
| GVA shock, 2010-2007 | | | −0.008 | −0.014 | |
| (% change) | | | (−0.043) | (−0.074) | |
| Employment, 2010-2007 | | | 0.001 | 0.001 | |
| (% change) | | | (0.046) | (0.050) | |
| House price | | | | 0.008 | |
| (Index, 2008Q3) | | | | (0.093) | |
| HP change | | | | 0.221 | |
| (2010Q1 - 2008Q3, %) | | | | (1.493) | |
| LTI | | | | −3.728 | |
| (At origination) | | | | (−0.845) | |
| Region fixed effects | Yes | Yes | Yes | Yes | Yes |
| Specification | IV | IV | IV | IV | IV |
| Observations | 8,115 | 8,115 | 8,115 | 8,115 | 7,491 |
| $R^2$ | 0.007 | 0.008 | 0.008 | 0.009 | 0.004 |
| *Note:* | | | | | *p<0.05; **p<0.01; ***p<0.001 |

Regressions are weighted by employment and standard errors are clustered at the local-authority level. There are 10 regions and 343 local authorities. GVA shocks are constructed using the neighborhood share of employment in each of the 17 main industrial sector categories and regional GVA indices. House price changes are from the ONS local-authority series.

**TABLE 7.** Neighborhood Regressions by Establishment Type

| | Probability, pp | | Employment growth, pp | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | Born | Die | Intensive | Chain | Cars | Food | Shops |
| Cash-flow shock | 0.062* | −0.101*** | 0.210* | 1.028*** | 0.816** | 0.708*** | −0.007 |
| (£000) | (1.966) | (−4.700) | (2.009) | (3.703) | (2.628) | (2.855) | (−0.068) |
| Region fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,115 | 8,115 | 8,094 | 4,805 | 7,625 | 8,073 | 8,097 |
| $R^2$ | 0.050 | 0.020 | 0.009 | 0.020 | 0.008 | 0.024 | 0.004 |
| *Note:* | | | | | | | *p<0.05; **p<0.01; ***p<0.001 |

Dependent variable for the first two columns is the increased probability of an establishment being born or dying between 2007 and 2010. In the third column, only establisments that employ workers in both years are included. Regressions are weighted by employment and standard errors are clustered at the local-authority level. There are 10 regions and 343 local authorities.

**TABLE 8.** Establishment-level Regressions, Intensive Margin

| | Employment growth, pp | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) All | (2) Chain | (3) Cars | (4) Food | (5) Shops | (6) 1 emp | (7) 2-4 emps | (8) 5-9 emps | (9) 10+ emps |
| Cash-flow shock (£000) | 0.210 (1.916) | 0.327** (2.721) | 0.615*** (2.996) | 0.366 (1.081) | 0.078 (1.177) | 0.576* (2.247) | 0.415*** (4.749) | 0.252*** (3.530) | 0.142 (1.071) |
| Region fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 249,276 | 26,815 | 71,168 | 151,293 | 14,520 | 34,169 | 99,313 | 65,093 | 50,962 |
| Employment in 2007 | 4.44m | 0.36m | 0.44m | 1.31m | 2.72m | 0.08m | 0.56m | 0.82m | 2.98m |
| *Note:* | | | | | | | | | *p<0.05; **p<0.01; ***p<0.001 |

Regressions include all establishments that employed workers in 2007 and 2010. They are weighted by establishment employment and standard errors are clustered at the local-authority level. There are 10 regions and 343 local authorities. The final row indicates overall employment in each category in 2007.

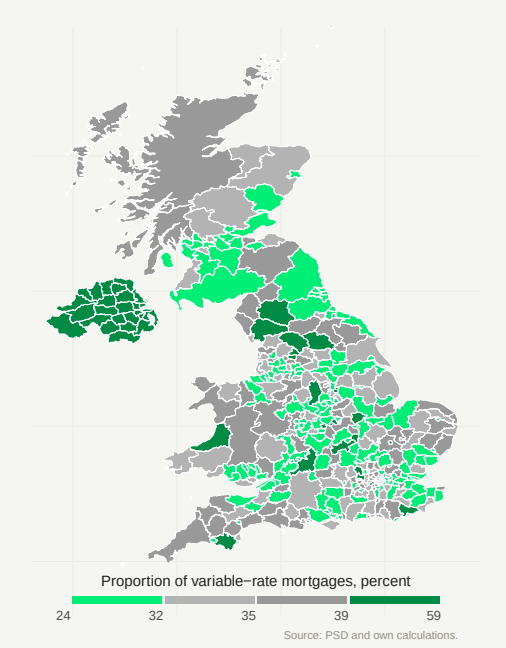
**TABLE 9.** Establishment-level Regressions, Extensive Margin

| | (1) All | (2) Chain | (3) Cars | (4) Food | (5) Shops | (6) 1 emp | (7) 2-4 emps | (8) 5-9 emps | (9) 10+ emps |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Probability of birth, % | | | | |
| Cash-flow shock | 36.1 | 39.2 | 28.5 | 44.9 | 32.5 | 50.3 | 37.1 | 31.5 | 28.0 |
| at $10^{th}$ percentile | (385.6) | (96.5) | (99.0) | (265.2) | (270.3) | (204.2) | (247.1) | (175.9) | (139.1) |
| Cash-flow shock | 36.8 | 39.8 | 28.5 | 44.7 | 33.5 | 50.8 | 37.3 | 32.9 | 29.3 |
| at $90^{th}$ percentile | (341.2) | (89.1) | (79.8) | (223.1) | (246.9) | (171.5) | (215.2) | (159.9) | (127.2) |
| Region fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 392,068 | 20,673 | 37,492 | 128,987 | 225,589 | 62,398 | 157,828 | 100,895 | 70,947 |
| | | | | | Probability of death, % | | | | |
| Cash-flow shock | 40.6 | 29.5 | 36.7 | 48.4 | 37.3 | 50.7 | 43.9 | 35.4 | 28.1 |
| at $10^{th}$ percentile | (392.8) | (68.0) | (108.8) | (255.3) | (282.0) | (190.4) | (271.4) | (174.8) | (124.3) |
| Cash-flow shock | 40.5 | 34.2 | 37.1 | 46.8 | 37.0 | 49.5 | 45.0 | 36.4 | 29.1 |
| at $90^{th}$ percentile | (336.6) | (60.6) | (90.5) | (204.3) | (248.1) | (159.0) | (235.6) | (153.3) | (107.6) |
| Region fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 419,445 | 18,219 | 42,504 | 136,146 | 240,795 | 68,501 | 178,344 | 101,338 | 71,262 |
| *Note:* | | | | | | | | | $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001 |

Regressions report IV probit specifications for the probability of an establishment being born or dying between 2007 and 2010. To aid interpretation, the figures reported are the absolute probabilities at different percentiles of cash-flow shock. Standard errors are clustered at the local-authority level. There are 10 regions and 343 local authorities.

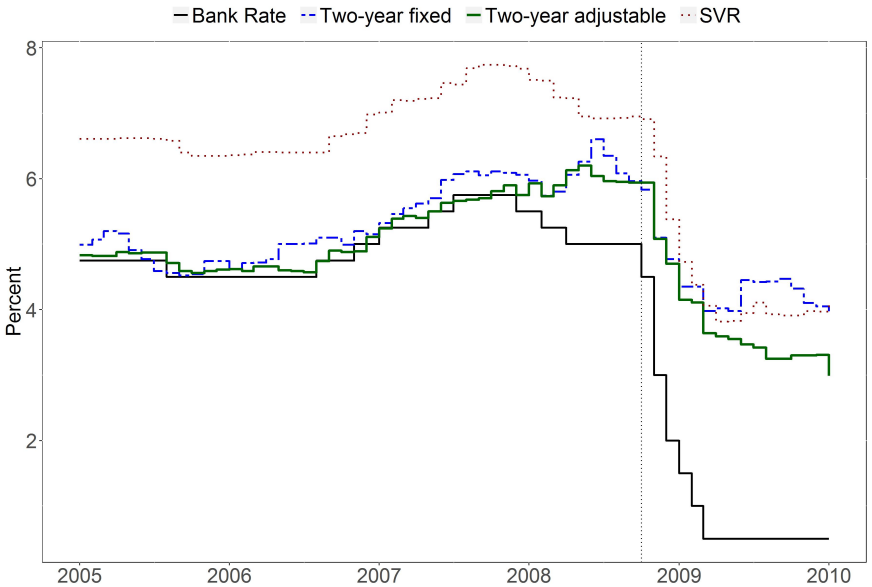
# 9 Figures

**Figure 1.** Distribution of Mortgages in July 2008



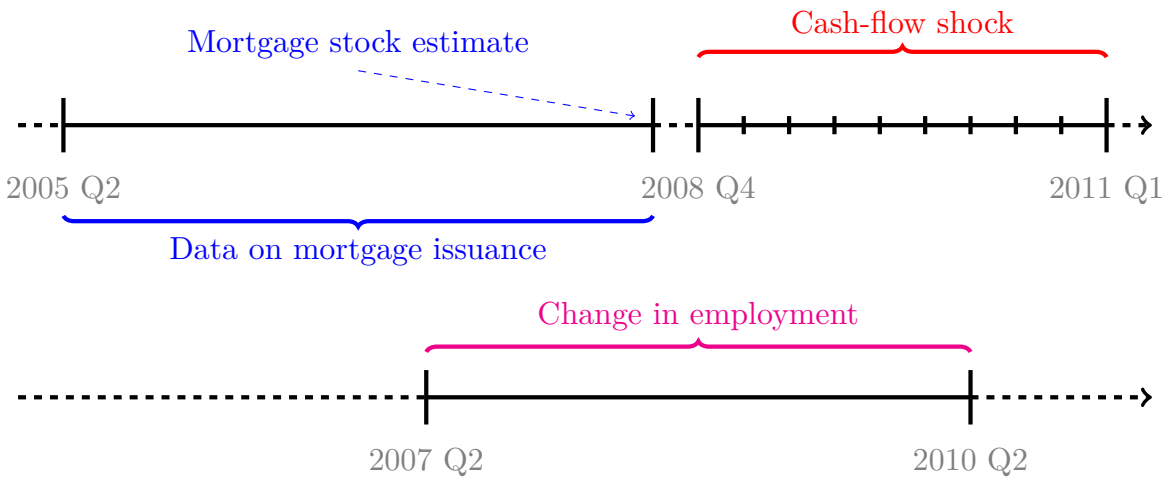

Source: PSD. Figure shows proportion of adjustable-rate mortgages at origination. Color breaks denote quartiles and 389 local authorities are shown.

**Figure 2.** Mortgage Interest Rates




Source: Bank of England. The first series shown is Bank Rate. From the Bank of England quoted rates series (with identifying code in brackets): 2-year fixed 75% LTV mortgage (IUMBV34), 2-year adjustable 75% LTV mortgage (IUMBV48) and the Standard Variable Rate (IUMTLMV).

**Figure 3.** Empirical Strategy Timeline




The figure shows the timeline for the central specification. I construct an estimate of the stock for the beginning of 2008Q3 using information on mortgages issued since 2005Q2. I then calculate the cumulative cash-flow shock associated with lower mortgage payments for every mortgagor over for the nine quarters after the start of 2008Q4. The dependent variable of the main regression is the percentage change in employment between April 2007 and April 2010. Figure 11 shows the coefficients for other employment windows using the same shock.

# 10 Appendix for Online Publication

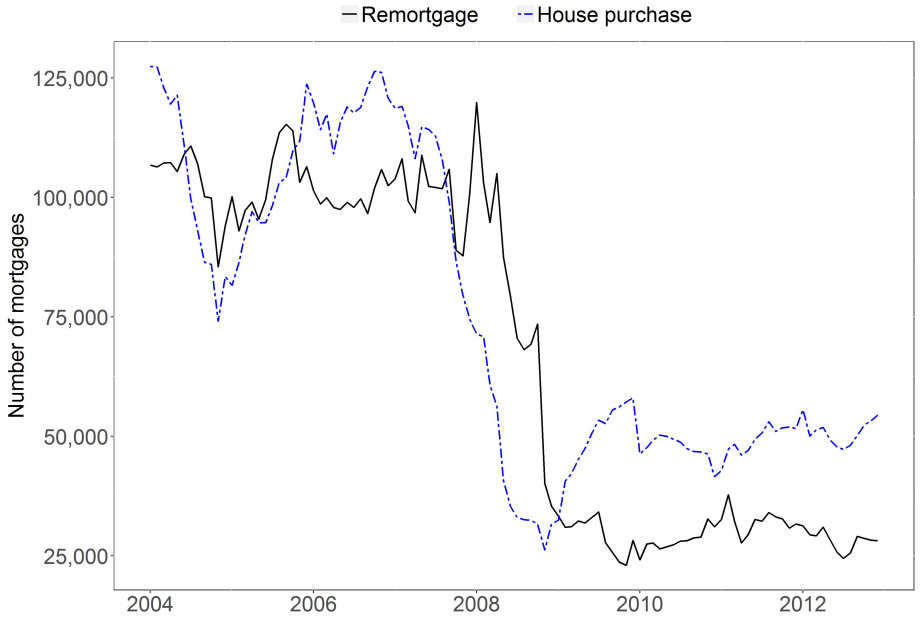
## 10.1 Mortgage Stock Construction

This section describes how I construct my cash-flow shocks based on the PSD mortgage origination data. The PSD is administrative data, reported by lenders to the Financial Conduct Authority for all but a few primary residential mortgages in the United Kingdom.[44] To minimise measurement error I remove mortgages with a mortgage term of less than 5 years, a loan-to-income ratio greater than 20 or a loan-to-value ratio of greater than 200. This removes about 3.7 percent of the data. I also drop business mortgages (only 0.25 percent of mortgages), as well those held by a social buyer, not known, or other (another 4.8 percent of mortgages).

In order to estimate the stock of mortgages in the summer of 2008 I must remove superseded mortgages from the origination data to prevent double counting. Removing previous

[44]The PSD only provides information on the stock of mortgages after 2015.

**Figure 4.** Mortgage Approvals

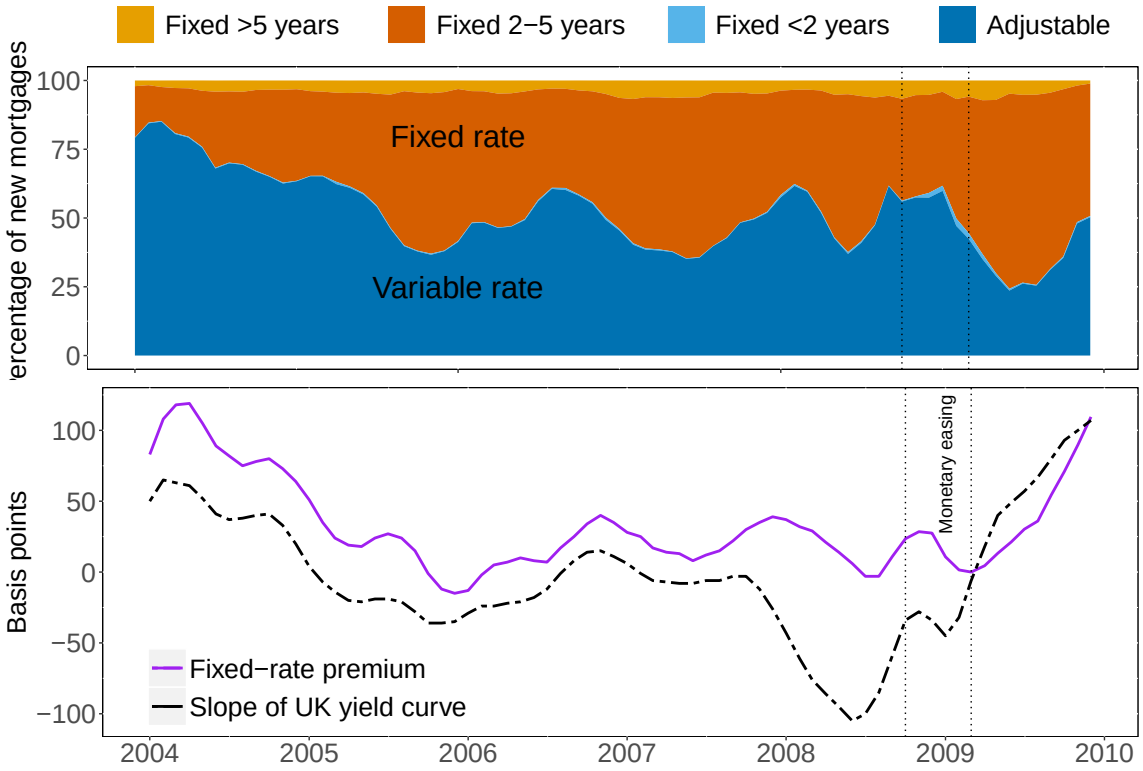



Source: Bank of England. The series correspond to the seasonally adjusted data for housing remortgage (B4B3) and housing purchase (VTVX) from the Bank of England Statistical Interactive Database.

refinancing transactions requires matching birth dates and post codes and keeping the latest transaction before July 2008. Since postcodes typically cover around 15 households, this process rarely yields false matches (which arise in a small number of cases when the designated primary borrower changes between refinancing events). Removing loans that were paid off when a home owner moved houses is a little more involved. I do this using a three-way match on the (1) birth date, (2) transaction date and (3) post code following the steps outlined in Chakraborty et al. (2017).

Because the data relies on lender reporting, there will sometimes be gaps and errors in the data due to mis-reporting or fields that are optional. For example, some mortgages will not include the initial interest rate or the length of initial period governing the behavior of the interest rate. Note that very few mortgages are missing information about whether the interest rate is fixed or adjustable (less than 0.5 percent).

**Figure 5.** Mortgage Issuance

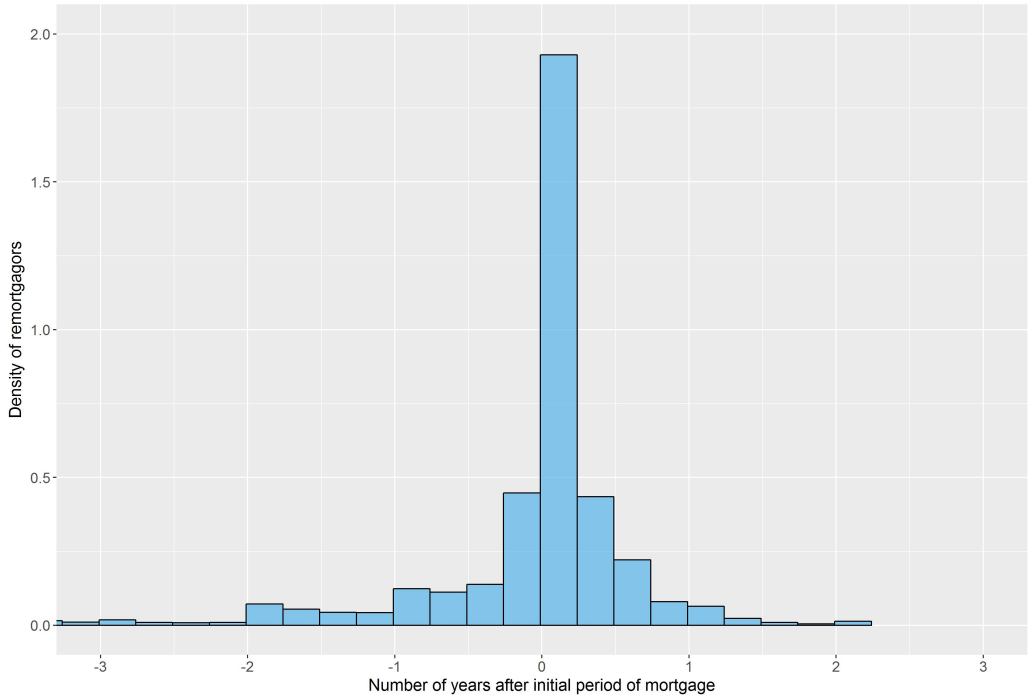



Source: Bank of England. The top panel of this figure shows the variation in mortgage-type issuance across time. These data are taken from Bank of England aggregated data and therefore have a slightly different make-up from the rest of the analysis (e.g., they include second-charge mortgages). The series correspond to Fixed for more than 5 years (CFMB9I2 and CFMB9I3), Fixed between 1 and 5 years (CFMB8R8), Fixed less than a year (CFMB8R7) and Variable rate (CFMB8R5). In practice, there is a negligible number of mortgages issued with contractual maturities of between 1 and 2 years. The bottom panel shows the time variation in the fixed-rate premium and the slope of the UK yield curve. The former is defined as the difference between the benchmark 2-year 75% LTV fixed-rate mortgage and the 2-year 75% LTV adjustable-rate mortgage. The latter is defined as the difference between 2-year UK Treasury rate and the 0.25-year UK Treasury rate. To allow for delays in the mortgaging process, both series are lagged by three months.

## 10.2 Imputing Missing Mortgage Variables

One important modification I must make is when the length of the initial period is missing. This is important because I use it to determine when a fixed rate mortgage will reset to an adjustable rate. For a mortgage originally on an adjustable rate, the initial period will determine when the mortgage reverts to the Standard Variable Rate (also an adjustable rate, but usually with a higher level and slightly slower pass-through from policy rates). 52 percent of the final sample of fixed-rate mortgages are missing the initial period (this field

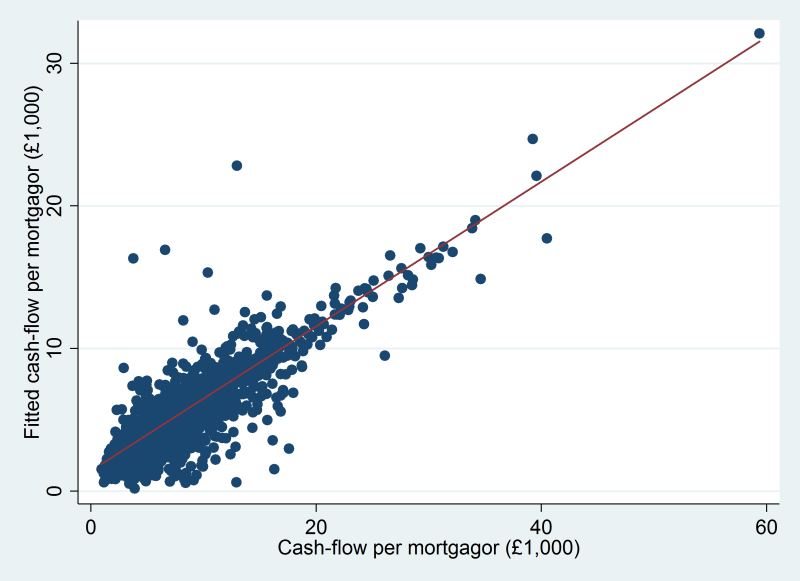
**Figure 6.** Timing of Remortgaging Activity




Source: PSD. This figure shows at what point mortgagors chose to remortgage their contract using matched remortgages in my stock. For example, someone who took out a two-year deal and remortgaged 25 months later would appear in the modal bucket

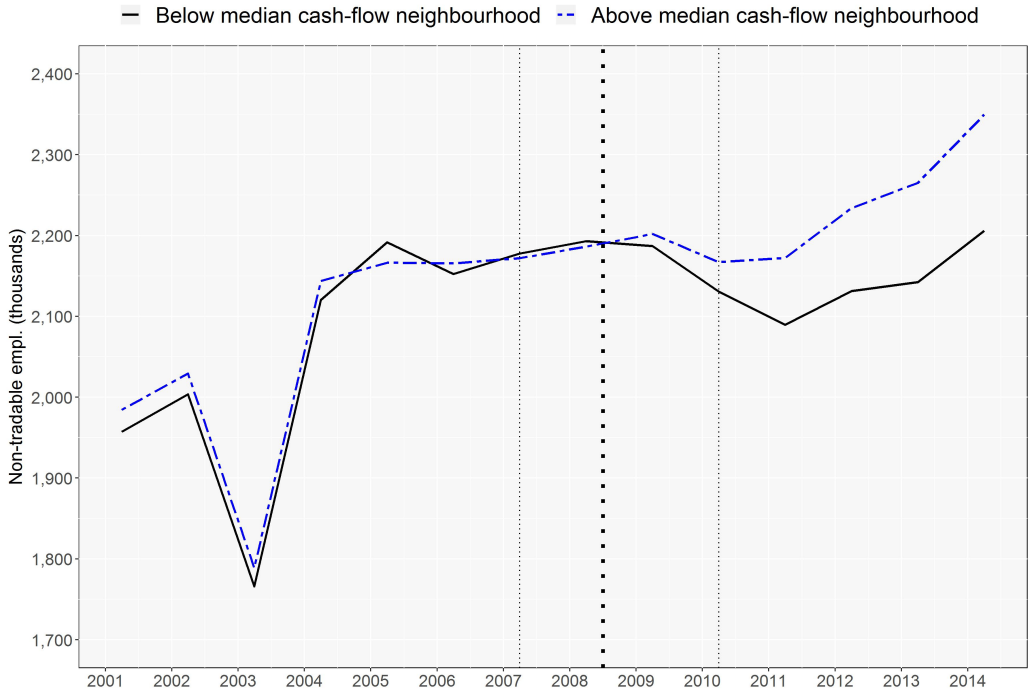
was optional before 2015). When it is missing, I impute it using a model on the observed distribution depending on whether the mortgage was originally on a fixed or adjustable rate at origination. The models are an ordered probit model, where the initial period can be 1, 2, 3, 4, or 5+ years. Included in the model are lender fixed effects, borrower age fixed effects, borrowing income category, the property value category, and an LTV category. I then use the predicted probabilities arising from this model to assign borrowers' their most likely initial period length (for all types of mortgage). The structure, competitiveness and national reach of UK mortgage lenders during this time meant that the sample of mortgages with a known initial period has very similar characteristics to that of the full sample, and the modal initial period was two years.

**Figure 7.** Neighborhood Instrument



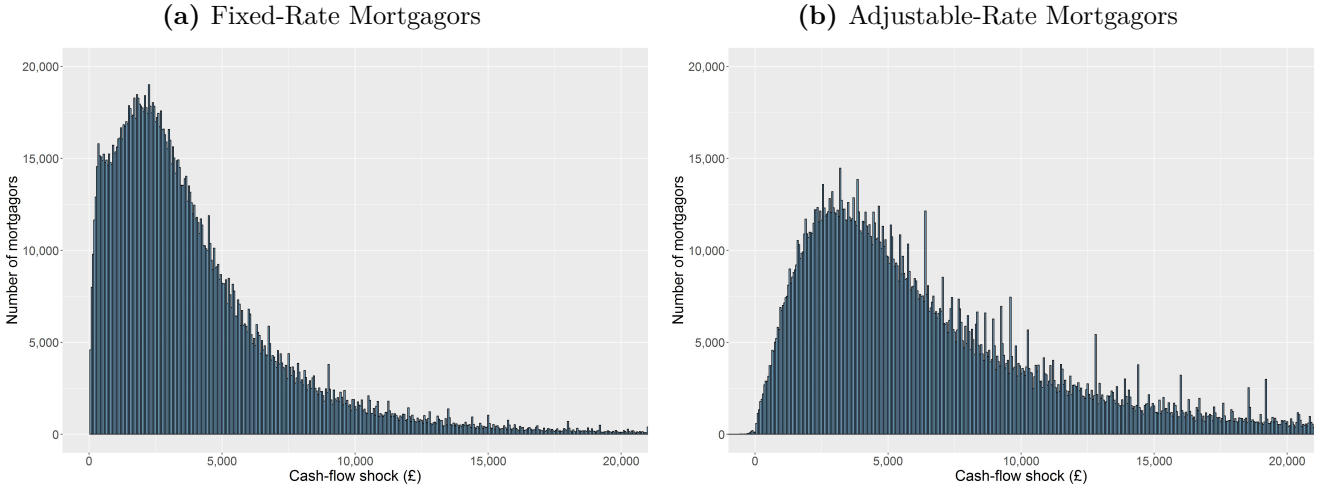

Source: PSD. This figure shows a scatter plot of the average cash-flow shock per mortgagor (2008Q3-2010Q4) versus the predicted cash-flow shock using the the temporal distribution of mortgaging activity for 8,000 wards.

**Figure 8.** Employment Trends and Predicted Cash-flow Exposure



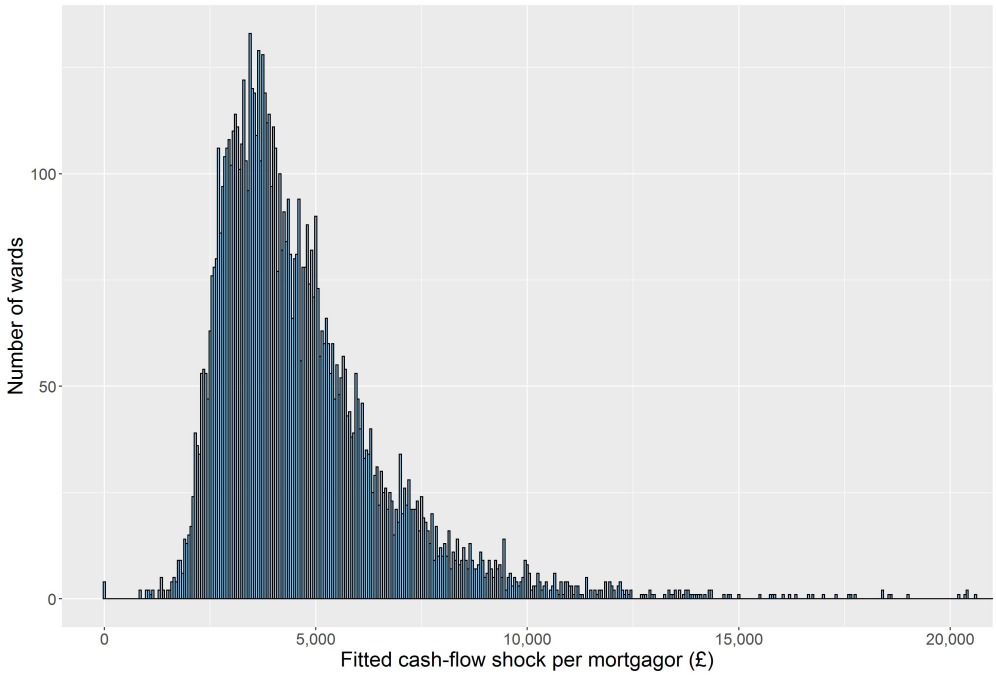

Source: PSD and BSD. This figure shows total employment in the locally non-tradable sector split by wards above (blue dashed) and below (black solid) the median predicted ward cash-flow shock. Narrow vertical dotted lines denote the points at which employment growth is measured in the baseline specification. Thicker dotted line indicates where mortgage stock is taken.

**Figure 9.** Individual Cash-flow Shock Distribution




Source: PSD. Around 5 million mortgages are shown across the two panels. Fixed-rate mortgagors are those on a fixed-rate contract as of 2008Q3 and does not indicate status at origination. Many fixed-rate mortgagors rolled on to the SVR at some point before the end of 2010. Buckets are £50 wide, though the £0-50 bucket has been excluded in the left-hand panel to make visual comparisons easier.

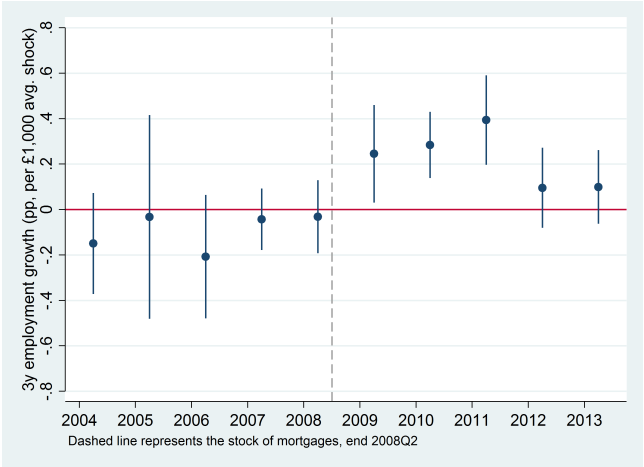
**Figure 10.** Neighborhood Cash-flow Shock Distribution



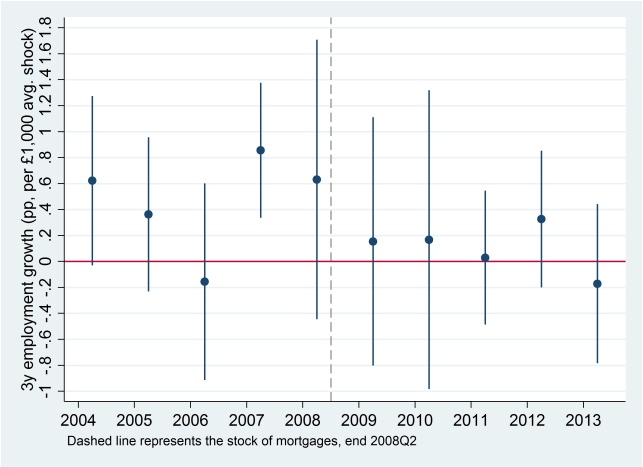

Source: PSD. This figure plots the mean predicted cash-flow shock across around 8,000 wards. The median value is around £4,100 and the mean is around £4,600.

**Figure 11.** Event-study Coefficient Estimates

**(a)** Locally Non-tradable Employment




**(b)** Manufacturing Employment




These figures show the main coefficients from IV regressions analogous to the main specification. The dependent variable is the three-year employment growth up until the date shown (so the coefficient in the third column of Table 5 is represented in 2010 on the left panel). Blue vertical lines show 90% confidence intervals.

## 10.3 Establishment Classifications

In 2007 there were around 21m private-sector employees. Around 4.4m were employed in what I define as locally non-tradable establishments and 1.6m in manufacturing establishments. This appendix gives some more details about those definitions.

The mechanical mapping from the US industrial categories leads to similar results to the spatial analysis carried out for the UK by Campos (2012). Of the thirty least geographically concentrated industries in the UK, only 11 relate to non-public and non-construction activities. The non-tradable definition used in the rest of this analysis captures all but two of these industries: wholesale activities and transport systems are excluded because they are unlikely to effectively capture local demand effects convincingly. Of the thirty most geographically concentrated industries in the UK, about half are captured in the main mapping from the existing literature; most are firms involved in some form of manufacturing. The other half contain industries associated with finance, transport, holiday recreation and professional services, many of which would plausibly fall under the intuitive definition of tradables in that the firms do not garner the majority of their sales from locally resident customers.

According to the primary classification system used in this study, locally non-tradable industry employment makes up 21% of the UK aggregate private sector employment, which is very similar to the share in the US. Of the 13 locally non-tradable industry groups, the largest employers are retailers of groceries, restaurants and other general merchandise stores. Unsurprisingly, these outlets tend to be concentrated in the most urban regions of the UK, in city centers such as London, Birmingham and Leeds but also in the suburban commuter zones and tourist destinations.

The first two columns in Tables A1 and A2 present the 25 locally non-tradable and 82 tradable classifications using the NAICS-12 system used in Mian and Sufi (2014). The third and fourth columns provide the closest matches to the SIC-03 system. The final column provides the share of employment as a proportion of total locally non-tradable and tradable

total employment, respectively.

The vintage of my data makes it is necessary to create a mapping between NAICS-12 and SIC-07, then back to SIC-03. Some NAICS-12 industrial classes therefore correspond to multiple SIC-03 codes. In the penultimate column of the tables I have listed the closest code matches.

## 10.4 Spending Out of Windfalls in the UK

To get at the question of how exactly people spend windfalls I follow Agarwal and Qian (2014) in looking at consumption responses to tax rebates using the UK's using the Living Costs and Food Survey. I use this cross-sectional survey of households to run the following regression:

$$c_i^j = \alpha + \beta \times \widehat{T}_i + \gamma_t + \delta \times X_i + \varepsilon_i \tag{10}$$

In Equation 10, $c$ is the measure of consumption for spending category $j$ and individual $i$. This is regressed on a constant, a tax rebate, $\widehat{T}$ and year fixed effects. In addition, I include individual controls and the regression controls for household income, mortgage size, last mortgage payment, measures of household size, and age and sex dummies for the household lead. The results in Table A3 show that mortgagors increase spending by 85 pence per pound of tax rebate. In particular the marginal propensity to consume in the restaurant and hotels category is around 0.25, shown in the second column, and is statistically significant at the 1 percent level. Since Agarwal and Qian (2014) find total marginal propensities to consume of around 0.4, the magnitudes in Table A3 do look large, though these windfalls are often small (the mean rebate over a two-week period is £15) and one might expect higher estimates with small windfalls (e.g., Fuster et al. (2018)). Due to the limited nature of the data and lack of clean identification, the modest aim of these regressions is to show that some supportive evidence that windfalls lead to spending in the local economy, and especially by mortgagors.

## 10.5 Full-time and Part-time Workers

In September 2009 the Office of National Statistics started the Business Register and Employment Survey (BRES) to improve the accuracy of establishment and sectoral employment data. This survey has information on the number of full-time and part-time workers employed by the surveyed establishments. In Table A7 I run the central specification on the BRES employment data to investigate locally non-tradable employment responses by type of worker. Because the survey starts after 2007, the dependent variable in these regressions is the change in employment between 2009 and 2011.

The first column shows that the point estimate for the total number of workers is similar to the main estimates. The lower accuracy likely reflects the smaller sample (although 8,000 wards are still reported, some wards have very few surveyed establishments). The second and third columns suggest that the increase in employment in response to a neighborhood cash-flow show was reasonably split between workers on full-time and part-time contracts.

**TABLE A1.** Locally Non-Tradable Industry Definitions

| NAICS-12 description | NAICS-12 code | SIC-03 description | SIC-03 code | Empl. share (2007, %) |
|---|---|---|---|---|
| Automobile Dealers | 4411 | Sale of new motor vehicles | 501 | 5.6 |
| Other Motor Vehicle Dealers | 4412 | Sale of motor vehicle parts and accessories | 503 | 2.0 |
| Automotive Parts, Accessories, and Tire Stores | 4413 | Sale, maintenance and repair of motorcycles and related parts and accessories | 504 | 0.3 |
| Furniture Stores | 4421 | Retail sale of automotive fuel | 505 | 1.2 |
| Home Furnishings Stores | 4422 | Retail sale in non-specialised stores | 521 | 27.0 |
| Electronics and Appliance Stores | 4431 | Retail sale of fruit and vegetables | 522 | 4.2 |
| Grocery Stores | 4451 | Retail of Medical and cosmetic | 523 | 2.4 |
| Specialty Food Stores | 4452 | Retail of specialised goods | 524 | 26.7 |
| Beer, Wine, and Liquor Stores | 4453 | Retail sale of books, newspapers, recreation and stationery | 525 | 0.4 |
| Health and Personal Care Stores | 4461 | Repair of personal and household goods | 527 | 0.6 |
| Gasoline Stations | 4471 | Restaurants and food service | 553 | 14.1 |
| Clothing Stores | 4481 | Beverage serving | 554 | 10.7 |
| Shoe Stores | 4482 | Catering | 555 | 4.5 |
| Jewelry, Luggage, and Leather Goods Stores | 4483 | | | |
| Sporting Goods, Hobby, and Musical Instrument Stores | 4511 | | | |
| Book Stores and News Dealers | 4512 | | | |
| Department Stores | 4521 | | | |
| Other General Merchandise Stores | 4529 | | | |
| Florists | 4531 | | | |
| Office Supplies, Stationery, and Gift Stores | 4532 | | | |
| Used Merchandise Stores | 4533 | | | |
| Other Miscellaneous Store Retailers | 4539 | | | |
| Restaurants and Other Eating Places | 7225 | | | |
| Special Food Services | 7223 | | | |
| Drinking Places (Alcoholic Beverages) | 7224 | | | |

**TABLE A2.** Manufacturing Industry Definitions

| NAICS-12 description | NAICS-12 code | SIC-03 description | SIC-03 code | Empl. share (2007, %) |
|---|---|---|---|---|
| Other food manufacturing | 3119 | Manufacture of bread; baked goods; sugar | 158 | 10.5 |
| Beverage manufacturing | 3121 | Manufacture of distilled potable alcoholic beverages | 159 | 2.6 |
| Tobacco manufacturing | 3122 | Manufacture of tobacco products | 160 | 0.3 |
| Fiber, yarn, and thread mills | 3131 | Preparation and spinning of cotton-type fibres | 171 | 0.3 |
| Fabric mills | 3132 | Manufacture of knitted and crocheted fabrics | 176 | 0.1 |
| Textile and fabric finishing and fabric coating mills | 3133 | Manufacture of leather clothes | 181 | 0.0 |
| Textile furnishings mills | 3141 | Dressing and dyeing of fur; manufacture of fur articles | 183 | 0.0 |
| Other textile product mills | 3149 | Manufacture of footwear | 193 | 0.3 |
| Apparel knitting mills | 3151 | Manufacture of panels and boards | 202 | 0.3 |
| Cut and sew apparel manufacturing | 3152 | Manufacture of pulp | 211 | 0.9 |
| Apparel accessories and other apparel manufacturing | 3159 | Printing of newspapers | 222 | 9.7 |
| Leather and hide tanning and finishing | 3161 | Manufacture of coke oven products | 231 | 0.0 |
| Footwear manufacturing | 3162 | Manufacture of industrial gases | 241 | 3.2 |
| Other leather and allied product manufacturing | 3169 | Manufacture of pesticides and other agro-chemical products | 242 | 0.2 |
| Pulp, paper, and paperboard mills | 3221 | Manufacture of paints, varnishes and similar coatings | 243 | 1.1 |
| Converted paper product manufacturing | 3222 | Manufacture of basic pharmaceutical products | 244 | 3.8 |
| Printing and related support activities | 3231 | Manufacture of other chemical products | 246 | 1.7 |
| Petroleum and coal products manufacturing | 3241 | Manufacture of rubber tyres and tubes | 251 | 1.6 |
| Basic chemical manufacturing | 3251 | Manufacture of plastic plates, sheets, tubes and profiles | 252 | 10.5 |
| Resins and synthetic fibers and filaments manufacturing | 3252 | Manufacture of flat glass | 261 | 1.7 |
| Pesticide, fertilizer, and other agricultural chemical manufacturing | 3253 | Production of abrasive products | 268 | 0.5 |
| Pharmaceutical and medicine manufacturing | 3254 | Manufacture of basic iron and steel and of ferro-alloys | 271 | 1.3 |
| Paint, coating, and adhesive manufacturing | 3255 | Manufacture of steel tubes | 272 | 0.7 |
| Soap, cleaning compound, and w.c. prep. manufacturing | 3256 | Cold drawing | 273 | 0.3 |
| Other chemical product and preparation manufacturing | 3259 | Manufacture of metal structures and parts of structures | 281 | 4.6 |
| Plastics product manufacturing | 3261 | Manufacture of central heating radiators and boilers | 282 | 0.7 |
| Rubber product manufacturing | 3262 | Manufacture of steel drums and similar containers | 287 | 3.8 |
| Clay product and refractory manufacturing | 3271 | Manufacture of non-vehicle engines and turbines | 291 | 3.9 |
| Glass and glass product manufacturing | 3272 | Manufacture of furnaces and furnace burners | 292 | 6.0 |
| Other nonmetallic mineral product manufacturing | 3259 | Manufacture of other machine tools | 294 | 0.9 |
| Iron and steel mills and ferroalloy manufacturing | 3311 | Manufacture of weapons and ammunition | 296 | 1.0 |
| Alumina and aluminum production and processing | 3313 | Manufacture of electric domestic appliances | 297 | 1.4 |
| Nonferrous metal (except aluminum) production and processing | 3314 | Manufacture of computers | 300 | 1.6 |
| Foundries | 3315 | Manufacture of electric motors, generators and transformers | 311 | 1.4 |
| Cutlery and handtool manufacturing | 3322 | Manufacture of insulated wire and cable | 313 | 0.6 |
| Boiler, tank, and shipping container manufacturing | 3324 | Manufacture of accumulators, primary cells and primary batteries | 314 | 0.2 |
| Hardware manufacturing | 3325 | Manufacture of lighting equipment and electric lamps | 315 | 1.0 |
| Spring and wire product manufacturing | 3326 | Manufacture of other electrical equipment | 316 | 2.2 |
| Machine shops and screw, nut, and bolt manufacturing | 3327 | Manufacture of audio and visual equipment | 323 | 1.0 |
| Other fabricated metal product manufacturing | 3329 | Manufacture of medical and surgical equipment and orthopaedic appliances | 331 | 2.0 |

| | | | | |
|---|---|---|---|---|
| Agriculture, construction, and mining machinery manufacturing | 3331 | Manufacture of electronic instruments | 332 | 3.5 |
| Industrial machinery manufacturing | 3332 | Manufacture of motor vehicles | 341 | 4.7 |
| Commercial and service industry machinery manufacturing | 3333 | Manufacture of bodies (coachwork) for motor vehicles | 342 | 1.5 |
| Ventilation, heating and commercial refrigeration equipment manufacturing | 3334 | Building and repairing of ships | 351 | 2.1 |
| Metalworking machinery manufacturing | 3335 | Manufacture of other transport equipment | 355 | 0.1 |
| Engine, turbine, and power transmission equipment manufacturing | 3336 | Striking of coins | 362 | 0.5 |
| Other general purpose machinery manufacturing | 3339 | Manufacture of musical instruments | 363 | 0.1 |
| Computer and peripheral equipment manufacturing | 3341 | Manufacture of sports goods | 364 | 0.3 |
| Communications equipment manufacturing | 3342 | Manufacture of professional and arcade games and toys | 365 | 0.4 |
| Audio and video equipment manufacturing | 3343 | Manufacture of brooms and brushes | 366 | 2.1 |
| Semiconductor and other electronic component manufacturing | 3344 | | | |
| Navigational, measuring, electromedical, and control instruments manufacturing | 3345 | | | |
| Manufacturing and reproducing magnetic and optical media | 3346 | | | |
| Electric lighting equipment manufacturing | 3351 | | | |
| Household appliance manufacturing | 3352 | | | |
| Electrical equipment manufacturing | 3353 | | | |
| Other electrical equipment and component manufacturing | 3359 | | | |
| Motor vehicle manufacturing | 3361 | | | |
| Motor vehicle body and trailer manufacturing | 3362 | | | |
| Motor vehicle parts manufacturing | 3363 | | | |
| Aerospace product and parts manufacturing | 3364 | | | |
| Railroad rolling stock manufacturing | 3365 | | | |
| Ship and boat building | 3366 | | | |
| Other transportation equipment manufacturing | 3369 | | | |
| Office furniture (including fixtures) manufacturing | 3372 | | | |
| Medical equipment and supplies manufacturing | 3391 | | | |
| Other miscellaneous manufacturing | 3399 | | | |

**TABLE A3.** Spending Response of Mortgagors to Tax Rebate Shocks

| | Total Spend | Consumption Expenditure, £ Restaurants and Hotels | Goods and Service | Food and Drink |
|---|---|---|---|---|
| Tax rebate, £ | 0.849* | 0.248** | 0.158 | 0.082* |
| | (2.21) | (2.83) | (1.65) | (2.35) |
| Household income, £000 | 0.088* | 0.013*** | 0.004 | 0.008* |
| | (2.25) | (3.78) | (1.29) | (2.25) |
| Mortgage balance, £000 | 0.001* | −0.000 | 0.000** | 0.001* |
| | (2.55) | (−0.21) | (2.91) | (2.55) |
| Last mortgage payment, £000 | −0.149 | 0.028 | 0.047* | −0.149 |
| | (−0.92) | (1.51) | (2.45) | (−0.92) |
| Household size, persons | 29.851** | 1.145 | 6.389** | 29.851** |
| | (2.93) | (0.80) | (3.24) | (2.93) |
| Number of workers in household | 39.503* | 10.244*** | 2.931 | 39.503* |
| | (2.43) | (4.30) | (1.28) | (2.43) |
| Rooms in accommodation | 54.194*** | 2.413* | 2.072 | 54.194*** |
| | (5.95) | (2.17) | (1.55) | (5.95) |
| Cars owned | 54.844*** | 2.635*** | 5.960* | 54.844*** |
| | (3.70) | (1.25) | (2.42) | (3.70) |
| Year dummies | ✓ | ✓ | ✓ | ✓ |
| Age and Sex dummies | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.399 | 0.105 | 0.143 | 0.383 |
| Observations | 1,294 | 1,294 | 1,294 | 1,294 |
| *Note:* | | | | *p<0.05; **p<0.01; ***p<0.001 |

Source: Living Costs and Food Survey. Regressions show the spending response for survey respondents with a mortgage between 2006 and 2017. Survey responses are record of expenditure in the previous two week period. Only households reporting a tax rebate above £1 are reported.

**TABLE A4.** Worker Statistics in 2010

| | Gross annual wage, £ | | | | Mean | | | |
|---|---|---|---|---|---|---|---|---|
| Sector | Mean | $25^{th}$ pctl | Median | $75^{th}$ pctl | Age | Male (%) | Hours (week) | N |
| Vehicle repair | 22,600 | 13,700 | 20,000 | 26,000 | 41.8 | 80.9 | 41.3 | 696 |
| Retail trade | 13,400 | 5,800 | 10,400 | 16,000 | 38.9 | 36.5 | 29.6 | 4,581 |
| Food and drink | 10,700 | 4,900 | 7,800 | 13,800 | 35.0 | 41.3 | 28.0 | 1,536 |
| All other sectors | 25,300 | 13,200 | 21,000 | 32,000 | 42.6 | 48.8 | 37.0 | 41,487 |

Source: Labour Force Survey. This table summarizes worker characteristics by sector using the 2010 LFS. Numbers have been scaled up to annual equivalents to aid interpretation.

**TABLE A5.** Correlates of Predicted Cash-flow Shock Across Neighborhoods

| Variable | Mean | N |
|---|---|---|
| Cash-flow shock | 0.907 | 8,125 |
| Adjustable-rate mortgage share | 0.466 | 8,125 |
| Number of households | -0.022 | 8,125 |
| Number of mortgagors | -0.021 | 8,125 |
| GVA per capita | 0.237 | 8,125 |
| Manufacturing employment share | -0.118 | 8,125 |
| Change in GVA (2007-10) | 0.185 | 8,125 |
| Employment change (2007-10) | -0.058 | 8,125 |
| House price index (2008Q3) | -0.614 | 8,125 |
| House price change (2008Q3-2010Q4) | 0.390 | 8,125 |
| LTI at origination | 0.397 | 8,125 |
| Non-tradable employment (2007) | 0.063 | 8,125 |
| Non-tradable employment (2010) | 0.072 | 8,125 |

Source: These are the same as Table 4

**TABLE A6.** Additional Neighborhood Robustness Checks

| | Employment growth | | | | |
|---|---|---|---|---|---|
| | pp | | No. | pp | |
| | (1) | (2) | (3) | (4) | (5) |
| | Region Cluster | Equally Weighted | Linear Difference | Drop large Cash flow | Drop large Employment |
| Cash-flow shock | 0.335*** | 0.209 | 3.449*** | 0.470 | 0.206 |
| (£000) | (3.393) | (1.903) | (4.117) | (1.694) | (1.471) |
| Region fixed effects | Yes | Yes | Yes | Yes | Yes |
| Specification | IV | IV | IV | IV | IV |
| Observations | 8,115 | 8,115 | 8,115 | 7,283 | 7,281 |
| $R^2$ | 0.007 | 0.005 | 0.003 | 0.005 | 0.004 |
| *Note:* | | | *p<0.05; **p<0.01; ***p<0.001 | | |

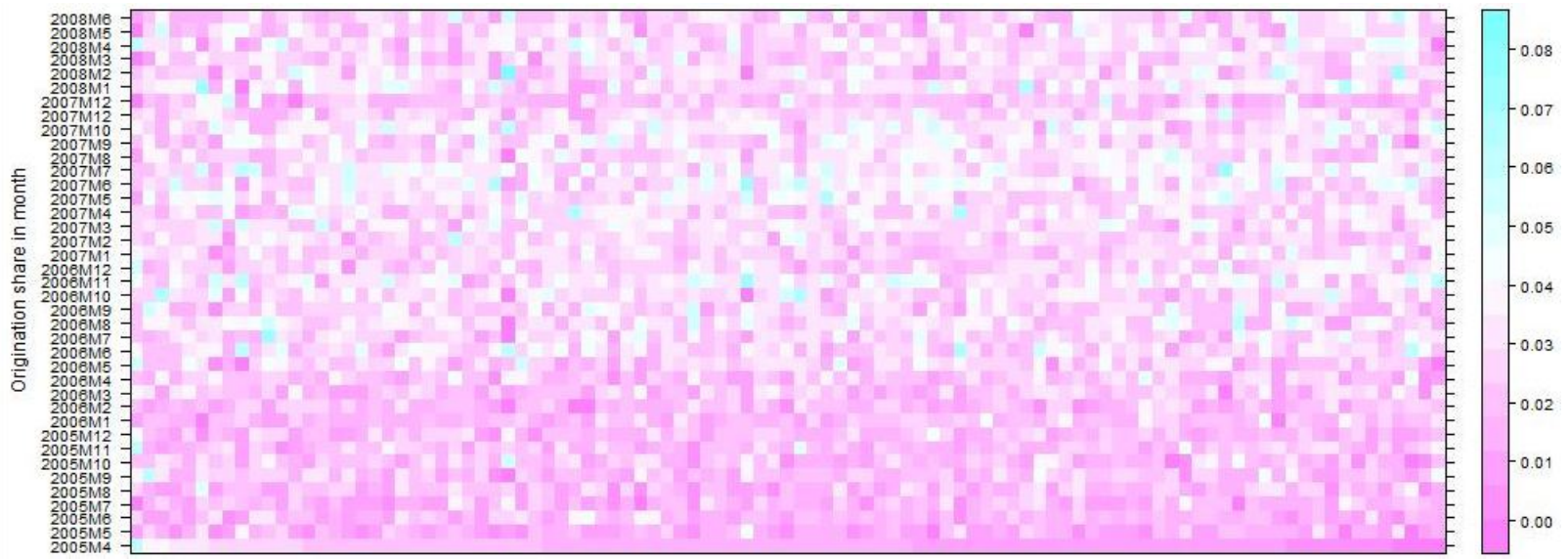
Regressions are generally weighted by employment and standard errors are clustered at the local-authority level. There are 10 regions and 343 local authorities. The first column clusters standard errors by the 10 regions. The second columns weights all observations equally. The third column takes the linear difference between employment in 2010 and 2007 as the dependent variable. The fourth and fifth column drop neighborhoods in the top quartile cash-flow shock and 2007-employment top quartile, respectively.

**TABLE A7.** Employment Response by Worker Type

| | Employment growth, pp | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Total | Full-time workers | Part-time workers |
| Cash-flow shock | 0.347* | 0.438* | 0.281 |
| (£000) | (2.220) | (2.475) | (1.758) |
| Region fixed effects | Yes | Yes | Yes |
| Specification | IV | IV | IV |
| Observations | 7,936 | 7,935 | 7,935 |
| $R^2$ | 0.012 | 0.013 | 0.014 |
| Employment in 2007 | 2.85m | 1.29m | 1.54m |
| *Note:* | | | *p<0.05; **p<0.01; ***p<0.001 |

Dependent variable is the neighborhood-level locally non-tradable employment growth between September 2009 and September 2011 using results from the Business Register and Employment Survey (BRES). This survey captures around two thirds of locally non-tradable employment, primarily from larger enterprises, with establishments belonging to a chain. Regressions are weighted by neighborhood employment and standard errors are clustered at the local-authority level. There are 10 regions and 343 local authorities.

**Figure A1.** Variation in the Share of Mortgages Issued by Month of Origination across Wards




Source: PSD. This figure plots the temporal distribution of the share of mortgages issued in each month (rows) for a sample of 100 neighborhoods (columns). The sample is ordered by the relative share of morgages issued in 2005M4, so the final row is a gradual color change from left to right. Variation in the predicted cash-flow shock arises from this temporal distribution.