Inertia and Pass-Through in Retail Deposit Markets

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This paper investigates heterogeneous pass-through of monetary policy rates to variable-rate savings accounts using monthly account-level panel data from a Dutch comparison website. I find incomplete and delayed pass-through that varies widely across banks but even account products offered by the same bank. Bank-specific factors explain around half of the variation in pass-through rates. Within banks, internet-managed and newer accounts capturing market segments with more flexible consumers exhibit substantially higher pass-through compared to regular and older accounts. This suggests an important role of inertia for the monetary transmission channel.

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I. Introduction

The effective transmission of monetary policy rates to retail bank rates is a central concern for monetary policy and has gained even further importance after the 2008 financial crisis. In absence of frictions and under perfect competition, pass-through of changes in policy rates should be immediate and one-to-one. A large number of studies document, however, delayed and partially incomplete pass-through on macro level.[1] Uncovering potential micro determinants of this price stickiness has spured a number of micro studies relating bank-level heterogeneity in pass-through rates to banks' financial structure, market power, or their operational efficiency.

In this work, I study pass-through of monetary policy rates to variable-rate savings accounts using monthly account-level panel data from a Dutch comparison website. I find substantial heterogeneity in pass-through rates across banks but even account products offered by the same bank. Bank-specific factors explain around half of the cross-sectional variation in account-level pass-through rates. Within banks, internet accounts capturing market segments with more flexible consumers exhibit substantially higher pass-through compared to regular accounts, while older accounts with a higher share of inert customers show significantly lower pass-through than newer accounts. This suggests an important role of inertia for the monetary transmission channel.

My results are important for several reasons. First, they shed light on how monetary policy impacts deposit pricing as a uniquely stable source of bank funding. Second, recent work provides evidence for a direct link between market power of banks, deposit supply, and the supply of bank lending in the economy.[2] My findings suggest inertia as an important force behind the ability of banks to exercise their market power. Last, from a policy perspective, measures to improve digitilization across the population might have unexpected positive effects for the monetary transmission mechanism.[3]

Isolating the effect of inertia on the transmission mechanism is challenging, since the dynamics of price adjustment depend on both supply and demand conditions (Kashyap and Stein (2000)). Thus, for example, the impact of market structure on pass-through is ambiguous. If concentration arises from market power of banks, this should negatively impact pass-through (structure-conduct-hypothesis). On the other hand, if differences in operational efficiency drive concentration, the reverse effect is possible (efficiency hypothesis).[4] Moreover, any differences in bank characteristics, e.g., financial structure or reputation, are likely correlated with differently inert customer bases resulting in an

[1] Mester and Saunders (1995), Kleimeier and Sander (2000), Mojon (2000), Toolsema, Sturm and De Haan (2001), De Bondt (2005), Sørensen and Werner (2006), and Gigineishvili (2011).

[2] Drechsler, Savov and Schnabl (2016) call this mechanism the deposit channel.

[3] For instance, the European Commission in the course of its single digital market initiative aims to promote the roll-out of broadband infrastructure and enhance digital skills across the population. See, e.g., https://ec.europa.eu/digital-single-market/en/policies/shaping-digital-single-market

[4] See, e.g., Berger and Hannan (1989).

omitted variable problem.

To separate the effect of inertia on monetary transmission from bank-level determinants, I follow a two-step approach. First, I estimate a heterogenous panel error correction model relating the adjustment of changes in retail rates to contemporaneous and lagged changes of the marginal costs of funds as measured by the EONIA rate. This yields a cross-sectional distribution of account-level pass-through rates. Second, I regress this distribution on bank fixed effects and proxies for inertia including an internet account dummy and year of account introduction.[5] The identifying assumption for this within-bank estimation is that the marginal costs of accounts do not substantially differ for a given bank, while within-bank differentiation is mainly driven by price discrimination among consumers of different inertia levels.

The results show incomplete, delayed, and highly heterogeneous pass-through. The average long-run pass-through is 27.5% ranging from 9.9% at the 25%-percentile to 44.1% at the 75%-percentile, while average short-run pass-through is close to zero in the first three months. Bank fixed effects explain around 55% of the variation in pass-through rates. Within banks, internet accounts have 15.3% higher long-run pass-through compared to regular accounts, while each additional year an account has been active in the market decreases long-run pass-through by 7.9% on average. This suggests that the high explanatory power of bank-level determinants used in a number of prior studies, at least, partially proxies for differently inert customer bases across banks.[6]

Related literature. A number of studies have analyzed the relation between monetary policy and competition using bank-level panel data. Neumark and Sharpe (1992) and Hannan and Berger (1991) are two early influental studies documenting the impact of market concentration on interest rate pass-through. Following their lead, the issue has been investigated by Cottarelli, Ferri and Generale (1995), De Graeve, De Jonghe and Vander Vennet (2004), De Graeve, De Jonghe and Vander Vennet (2007), Van Leuvensteijn et al. (2008), Gambacorta (2008), and Gropp, Kok and Lichtenberger (2014). These studies find that pass-through varies across products of different maturity, the competitive environment, and bank-level determinants such as market power, capital structure, risk profile, or the degree of relationship lending. I contribute to this literature in several ways. First, I analyze heterogeneous pass-through at the more granular

[5] Deuflhard, Georgarakos and Inderst (2017) show that more financially literate consumers are more likely to select internet accounts, while Deuflhard (2016) shows that frequent online banking users exhibit lower inertia in savings account choice. Following the logic in Klemperer (1995), I proxy account age by counting the number of years an account has been in the market since 2004. While banks cannot directly price discriminate between existing and incoming customers, they can segment their pricing schedules depending on the share of locked-in consumers in different account products. New products will first be marketed to a higher share of incoming customers. As the product matures over time, the share of locked-in customers gradually increases giving firms more pricing power over older products.

[6] For example, De Graeve, De Jonghe and Vander Vennet (2007) find that liquid and highly capitalized banks have substantially lower pass-through which are likely the banks with the most inert customer bases.

level of individual savings accounts and relate the estimates to account-specific determinants. Second, while prior work finds heterogeneous pass-through for financial products of different maturity, it has been unable to separate term structure effects from the composition of the customer base in different products. In contrast, I find highly heterogeneous pass-through for account products of the same maturity offered by the same bank which can be partially explained by proxies for the share of inert customers in different account products.

Several more recent studies empirically assess pass-through determinants recognizing the identification problem arising from the simultaneous interplay of supply and demand conditions. Drechsler, Savov and Schnabl (2016) exploit within-bank variation in concentration across branches to identify the deposit channel of monetary policy. Scharfstein and Sunderam (2015) study the effect of competition in mortgage markets using a matching procedure to compare high- and low-concentration counties. In contrast, I exploit variation in pass-through rates within banks for a given market. Two recent studies relate the transmission channel to frictions. Driscoll and Judson (2013) show that a simple menu cost model can explain asymmetric price adjustment behaviour in deposit rates. Yankov (2017) studies the relation of search costs and monetary transmission in a structural framework. This work takes a reduced-form approach but separates the effect of inertia from other sources of market power on bank level.

The rest of the paper is organized as follows. Section II describes the Dutch deposit markets. Section III describes the data. Section IV provides pricing evidence of inertia. Section V introduces the empirical framework for the pass-through model. Section VI analyzes determinants of inertia. Section VII concludes.

II. The Dutch deposit market

The Dutch central bank distinguishes between three main types of deposit accounts: While checking accounts are used for transactional purposes, savings accounts and fixed-term deposits receive interest with the former being redeemable any time and the latter being held over an agreed maturity. In this study, I focus on savings accounts which constitute the most important form of savings for Dutch households.[7] As savings accounts are fully flexible, this allows to meaningfully compare prices in the market by homogenizing the maturity dimension.

Almost all banks offer multiple differentiated types of savings accounts which can be roughly partitioned across two dimensions. First, accounts are either internet managed or not. Internet accounts are fully managed online by the depositor, offer only limited banking services, and, thus, require a higher degree of customer sophistication. In

[7]See, e.g., DNB (2015).

addition, accounts can be restricted or not. These restrictions include, for example, withdrawal limitations, minimum balance requirements, or the requirement of a salary account at the same bank. Table 1 shows that this within-bank differentiation can result in quite large account menus. For example, ABN Amro offers in total 10 accounts, Fortis Bank 3, and SNS Bank 20 accounts over the entire sample period. Most banks offer each of the four account types with the exception of Fortis Bank offering no restricted internet accounts and Rabobank offering no unrestricted internet accounts. As shown in the last row, the two most common accounts are unrestricted (35) and restricted plain accounts (43), followed by unrestricted (22) and restricted internet accounts (14).

The Dutch deposit market is considered one of the most concentrated in the EU area. The difficulty of new entrants to gain significant market share in combination with low switching rates has prompted concerns both by the Dutch central bank and the competition authority. A survey conducted by the latter revealed that 50% of consumers above 18 had never switched their savings account, the majority of which were customers of large banks.[8]

III. Data description

My main data source is a weekly product-level panel data set on annual interest rates for savings accounts of all Dutch banks from April 2004 to December 2012 provided by a major Dutch financial institution. The data set covers in total 55 banks offering 231 savings accounts. For each savings account, it contains the weekly interest rate for eleven different amount brackets ranging from €0 - €1,000 to €45,000 or more.[9] I retrieve addtional data on the existence of various savings account restrictions provided by the Dutch Internet comparison website 'SpaarInformatie'. Apart from internet accounts, the information from the comparison website allows to distinguish in total six main restrictions such as balance requirements or withdrawal limitations.[10]

I impose a few sample restrictions to perform my analysis. First, similar to previous macro studies, I aggregate the data to the monthly level to adequately capture pass-through over a sufficiently long time horizon with a reasonable number of parameters.[11]

[8] See, DNB (2009) and ACM (2014).

[9] The exact amount brackets are €0 - €1,000, €1,000 - €2,500, €2,500 - €3,500, €3,500 - €4,500, €4,500 - €7,000, €7,000 - €8,000, €8,000 - €9,000, €9,000 - €10,000, €10,000 - €25,000, €25,000 - €45,000, and more than €45,000. As some of these volume thresholds might fall within these ranges, I manually recover the exact amount thresholds whenever possible.

[10] (1) Accounts with minimum amount requirements offer either very low base rates or zero interest rate up to a certain volume threshold and higher rates above that threshold. (2) Accounts with lowest balance bonus give a bonus rate on the lowest account balance within a year or a quarter and yield a base rate on the remaining balance. (3) Accounts with balance growth bonus yield a bonus rate if the balance grows by a specified percentage amount per month or year. (4) Accounts with fixed deposit require a specified absolute deposit each month. (5) Accounts with withdrawal limitations / fees limit the maximum amount that can be withdrawn per month or comprise percentage fees for withdrawals (mostly 1% of the withdrawn amount). (6) Salary accounts are linked to a checking account at the same bank, which needs to be the income account.

[11] More precisely, I keep the rate of the last week of each month. The estimation results are quantitively

Second, I focus on accounts observed at least four years given the length of the lag structure employed in the estimation. This final sample covers in total 36 banks offering 114 savings accounts. In addition, to analyze pass-through the appropriate marginal costs of funds have to be determined. As the sample contains only variable-rate savings accounts, I select the EONIA rate as the marginal costs of funds. The EONIA rate is the 1-day average interest rate for all overnight unsecured lending transactions on the EURO zone interbank market which constitutes one of the main alternative funding sources for banks compared to instant-access deposits.[12] This has several advantages: First, compared to the ECB rate on the main refinancing operations, the EONIA rate is determined by market forces and, thus, changes more frequently. Second, analyzing pass-through in relation to a money market rate of the same maturity allows to disentangle pass-through of marginal cost changes from term structure effects.[13]

Figure 1 shows the evolution of average interest rates and the EONIA rate on a monthly basis from 2004 to 2013 by bank category (Panel A) and account type (Panel B). Panel A shows that smaller banks offer on average higher interest rates than the larger banks in most periods and seem to follow the changes in the EONIA rate more closely. Nevertheless, the adjustment behavior is quite sluggish, in particular, for average interest rates at ING Bank which seem to move quite disconnected from movements of the EONIA rate. Panel B shows that unrestricted and restricted internet accounts offer the highest rates and follow the EONIA rate closer. In contrast, unrestricted and restricted plain accounts have significantly lower rates and seem to adjust much slower.

IV. Pricing evidence of inertia

In this section, I provide pricing evidence consistent with the presence of inertia. As described in Klemperer (1995), inertia creates two opposing effects from the perspective of optimal dynamic pricing of banks. As banks can rationally expect that new customers become locked-in in the future, they face a trade-off between 'harvesting' and 'investing'. Harvesting describes the incentive of setting lower interest rates to exploit the existing customer base, while investing describes the incentive of pricing more aggressively to gain new customers. Even if banks cannot directly price discriminate between existing and incoming customers, they can segment their pricing schedules depending on the share of existing customers in different accounts. New products will first be marketed to a higher share of incoming customers. As the product matures over time, the share of locked-in customers gradually increases giving firms more pricing power for older products. As a result, new accounts should be initially sold at low (perhaps even below

similar when averaging over all weeks in a given month.

[12]For those accounts with restrictions slightly limiting liquidity, this can be seen as the closest approximation of the marginal costs of funds.

[13]See, e.g. De Bondt (2005) or De Graeve, De Jonghe and Vander Vennet (2007) for similar arguments.

marginal cost) prices, but sold at higher prices in later periods.

Figure 2 shows the distribution of interest rates in 2007 split between younger cohorts of accounts introduced 2004 or earlier and older cohorts of accounts introduced 2005 or later. There is substantial variation in interest rates for both groups. While the distribution of interest rates is much wider for older accounts with larger mass in the low interest rate region, the distribution of younger accounts is much thinner and shifted towards the higher interest rate region. This is consistent with the theoretical predictions that interest rates decrease as accounts age. Similiar to Ericson (2014), I run the following specification to shed light on the effect of inertia on pricing:

$$lnr_{it} = age_{it} + \gamma_t + X_i + u_{it} \tag{1}$$

where r_{it} is the account rate, age_{it} is account age since 2004 measured in years, X_i contains account type dummies and bank fixed effects, and γ_t are year-month fixed effects. Thus, the specification identifies the effect of account age on interest rates by comparing accounts of different ages in a given month removing any common time-varying unobserved heterogeneity conditional on the remaining covariates. Standard errors are clustered at the account level to allow for arbitrary serial correlation.

Table 2 shows the results. Model (1) gives the association of account age and interest rates controlling only for time fixed effects. Older accounts have substantially lower rates than younger ones, around 44% in their fourth year and 59% in their eighth year. This shows that the association of account age with interest rates is not merely due to changes in the composition of accounts toward accounts with higher interest rates or unobserved common time trends. Model (2) adds dummies for the four different account types, while Model (3) adds bank fixed effects.[14] Thus, the last model identifies the effect of account age on interest rates exploiting variation within banks over time. The coefficients for account age remain largely unaffected suggesting that the effect is not merely driven by different characteristics of accounts or the offering bank. Overall, the results indicate that firms likely incorporate inertia in their pricing consistent with an invest-and-harvest dynamic as described above.

V. Pass-through model

A. Methodology

My analysis of the pass-through of EONIA rates to retail bank rates takes into account that the aforementioned variables may be non-stationary. To test this empirically,

[14]The model does not contain account fixed effects due to the well-known inability to separately identify cohort, age, and year fixed effects.

I perform the Im, Pesaran and Shin (2003) unit-root test for the unbalanced interest rate panel. The test statistic of 4.42 indicates that the null hypothesis of a unit root cannot be rejected at all standard significance levels. My aim is to allow for heterogeneity in almost all aspects of account pricing. I, thus, additionally apply the panel cointegration test by Pedroni (1999) to test for a cointegrating relationship between retail bank rates and the EONIA rate which allows for full parameter heterogeneity. This left-sided residual-based test statistic is normalized to asymptotically follow a standard normal distribution and uses the left tail of the normal distribution to reject the alternative hypothesis. It is based on individual Engle-Granger cointegrating regressions representing a long-run relationship between retail and EONIA rates as follows:

$$r_{it} = c_i + \delta_i m_t + u_{it} \tag{2}$$

where r_{it} is the account rate, m_t the EONIA rate, $t = 1, .., T$ indexes time, and $i = 1, .., n$ denotes banks. The individual long-run pass-through coefficients are measured by δ_i, while c_i denotes account-specific mark-ups. Then, an error correction representation of the following form exists:

$$\Delta r_{it} = \alpha_i + \sum_{k=0}^{q} \beta_{ki} \Delta m_{t-k} + \gamma_i u_{it-1} + \epsilon_{it} \tag{3}$$

where r_{it} and m_t are defined as previously, and ϵ_{it} is a product-specific error term in month t. I determine the optimal lag length q using the Bayesian Information Criterion allowing for a maximum number of six lags comparable to previous studies (De Graeve, De Jonghe and Vander Vennet (2004), De Graeve, De Jonghe and Vander Vennet (2007), Gambacorta (2008), Gropp, Kok and Lichtenberger (2014)). The term $\gamma_i u_{it-1}$ captures the adjustment towards the long-run relationship, where $\gamma_i \in]-1, 0[$ confirms the presence of a cointegrating relationship. In all specifications, standard errors are clustered at the account level to allow for intragroup correlation in the error terms. The i-subscripts on the respective coefficients indicate the presence of heterogeneity. Following Swamy (1970), I fit a random coefficient model:

$$\theta_i = (c_i, \delta_i, \alpha_i, \beta_{1i}, ..., \beta_{qi}, \gamma_i) = \bar{\theta} + v_i \tag{4}$$

where v_i is random noise revolving around the mean estimate $\bar{\theta}$. Note that while the approach encompasses full heterogeneity, aggregate coefficients can be calculated as a weigthed average of the individual coefficients, where the weights, ω_i, are a function of the respective estimated covariances (Swamy (1970)). This implies that $\bar{\theta} = \sum_{i=1}^{N} \omega_i \theta_i$ for each parameter contained in $\bar{\theta}$. Thus, similar to De Graeve, De Jonghe and Vander Vennet (2007), the specification allows each account to exhibit different dynamics in reaction to changes in policy rates, while the traditional panel approach allows only for heterogeneity in the time-invariant individual-level effects. This allows to extract a full pass-through distribution from the data which can be related to both bank- and account-level determinants.

B. *Results*

In this section, I discuss the main estimation results. Table 3 shows the results of the primary specification and several robustness checks. The last two rows report the results of the cointegration and heterogeneity tests. I test the null of parameter homogeneity against the heterogeneous specification using a likelihood ratio test. The corresponding χ^2-distributed test statistic is 4076.82 with a p-value of 0.000 clearly rejecting the restrictions of the homogenous coefficient model. The panel augmented Dickey-Fuller test statistic of -3.47 indicates that the null hypothesis of no cointegration can be rejected at 1%-significance level. In the primary specification, the significant adjustment coefficient, γ_i, confirms the presence of a cointegration relationship consistent with the results of the previously employed cointegration test.

The results further show that account rates react only slightly in the first three months following a change in the EONIA rate as the coefficients on the contemporaneous and first two lags of the differenced EONIA rate are insignificant, while pass-through gradually picks up after three months. Nevertheless, after ten months only 27.5% of EONIA rate changes are passed through suggesting highly incomplete pass-through in the long-run. This is in line with prior studies analyzing pass-through of deposit products with similar maturities. For example, De Graeve, De Jonghe and Vander Vennet (2007) find an average of 53% for demand deposits, De Bondt (2005) find 41% for overnight deposits, and Gropp, Kok and Lichtenberger (2014) find pass-through between 20% and 30% after 6 months for demand and savings deposits.

To shed further light on the result of highly incomplete long-run average pass-through in this market, Figure 3 reports the distribution of the main parameters of interest over all time series on account level. The results show highly heterogeneous short- and long-run pass-through and confirm incomplete pass-through in the long-run. Short-run pass-through is rather symmetrically distributed both in the negative and positive domain with a mean slightly above zero. Surprisingly, some of the accounts even exhibit negative long-run pass-through being seemingly completely disconnected from movements in the EONIA rate. This finding suggests a strong countervailing force impacting pass-through rates as monetary policy rates should typically be seen as an opportunity cost of funds for banks. Last, the majority of the estimated adjustment speed parameters are distributed in the negative domain again comfirming the existence of a cointegrating relationship for the majority of accounts.

C. Robustness

I perform several robustness checks to analyze the sensitivity of my results displayed in Table 3. Robust (1) restricts all coefficients to be the same across the cross-sectional units which is the predominant approach in the macro literature. This decreases the estimated overall long-run pass-through to 22%. In contrast, De Graeve, De Jonghe and Vander Vennet (2004) find evidence for heterogeneity bias in the estimation of the speed of adjustment coefficients but no evidence for differences in long-run pass-through rates. Robust (2) shows estimates from the same specification but now restricts the sample to a balanced panel of accounts. If pass-through rates are time-varying, different pass-through rates of accounts observed over sub-periods might affect the results. While the estimation loses some efficiency due to the smaller sample size, the estimates are quite similar to the primary specification suggesting this does not severely impact the estimates. In addition, to assess whether the results, in particular, for the negative long-run pass-through rates found in the last section are driven by the distributional assumption imposed on the estimated pass-through parameters, I estimate an error correction model for each of the 114 accounts separately. For each time-series, I test the optimal number of lags according to the Bayesian Information Criterion allowing for a maximum of six lags as previously. The main parameter estimates are shown in Figure 4. Most parameters follow similar distributions as in the Swamy model with comparable means but slightly fatter tails. In particular, the finding of negative long-run pass-through for some accounts persists compared to the main specification suggesting the result is not simply driven by the distributional assumption of the Swamy model.

VI. Determinants

A. Methodology and Identification

In this section, I analyze determinants of the large heterogeneity in pass-through rates documented in Section III. The heterogeneous panel error correction model yields a cross-section of parameter estimates on account level. I regress this distribution for the mark-up as well as well long-run pass-through on time-invariant account- and bank-level characteristics as follows:[15]

[15] I also investigated heterogeneity in the other pricing measures which are, however, highly insignificant and, thus, not reported.

$$(\delta_i, c_i) = b_i + \alpha x_i + u_i \tag{5}$$

where b_i denote bank fixed effects and x_i are time-invariant account-level characteristics. First, it includes an internet account dummy. Higher interest bearing internet accounts likely compete for market segments with more flexible and sophisticated consumers. For example, Deuflhard, Georgarakos and Inderst (2017) show that more financially literate consumers are more likely to select internet accounts, while Deuflhard (2016) shows that frequent online banking users exhibit lower inertia in savings account choice. In addition, I include the number of years an account has been active in the market since the year 2004 to proxy for the share of locked-in consumers in different accounts consistent with the previous theoretical predictions.

Isolating the effect of inertia on the transmission mechanism is challenging, since the dynamics of price adjustment depend on both supply and demand conditions (Kashyap and Stein (2000)). Thus, heterogeneity in pass-through rates across banks might arise for a number of reasons including cost differences, demand elasticities, the curvature of demand, or the intensity of competition (Weyl and Fabinger (2013)). Because these factors interact, correlations between pass-through rates and bank-level characteristics such as market share or capital structure of banks as, e.g., in De Graeve, De Jonghe and Vander Vennet (2004), or De Graeve, De Jonghe and Vander Vennet (2007), likely suffer from omitted variable bias. For example, more liquid and better capitalized banks might well have more inert customer bases.

In contrast to prior work, the availability of account-level data allows me to completely shut down the bank-specific channel and exploit only variation in pass-through rates within a given bank across products holding bank-level factors fixed. The identifying assumption is that the marginal costs of accounts do not substantially differ across accounts within a given bank, while differentiation is mainly driven to price discriminate across consumers of different inertia levels and less to cater to consumers with different preferences. From an identification perspective, this strategy is similar in vein to Drechsler, Savov and Schnabl (2016). They exploit local variation in concentration across different branches of a given bank to identify the effect of market structure on deposit spreads. The authors also mention financial sophistication as one channel for the impact of market power on monetary transmission. They show that county-level proxies for financial sophistication including age, income, and college can partially explain differences in pass-through across branches located in different local markets within a given bank but are unable to convincingly separate financial sophistication from local market conditions. In contrast, I look at a single market holding market power of banks fixed.

B. Results

Table 4 shows two different specifications for both long-run pass-through rates and mark-ups. For the former, adding bank fixed effects alone explains only around 55% of the variation in long-run pass-through (Long-run (1)). This suggests that the high explanatory power of bank-level determinants such as capital structure or market power found in prior studies (De Graeve, De Jonghe and Vander Vennet (2004, 2007)) at least partially captures factors explaining within-bank heterogeneity in pass-through rates. In the second specification (Long-run (2)) adding account-specific determinants substantially increases the R-squared to 74%. The pass-through differentials across accounts are quite substantial. Internet accounts have 15.3% higher long-run pass-through compared to regular and restricted accounts. Moreover, older accounts have significantly lower long-run pass-through than newer accounts. Each additional year an account has been active in the market since 2004 increases the long-run pass-through by 7.9%. This is in line with the pricing predictions by Klemperer (1995) and suggests that demand side factors such as inertia likely play an important role in explaining incomplete monetary transmission.

For mark-ups, bank fixed effects explain around 40% of the variation (Mark-up (1)), which increases to 44% when adding the internet account dummy. Each additional year an account has been active in the market since 2004 increases the mark-up by 6.9% as shown in Mark-up (2). While this seems at odds at first with the on average lower interest rates for older accounts it is line with the much lower dependence on the EONIA rate of these accounts. In summary, the results suggest inertia as an important source behind the impact of market power on pass-through as documented by prior studies (De Graeve, De Jonghe and Vander Vennet (2004, 2007)). From a policy perspective, efforts to improve digitilization might have potentially surprising effects on the effectiveness of the monetary transmission channel.

C. Discussion

In this section, I discuss a number of concerns regarding the validity of the previously obtained results. First, the model identifies time-invariant pass-through rates over a longer time period including the financial crisis in the Netherlands resulting in a rapid decrease of interest rates compared to the prior period. Such a structural break might bias the estimated pass-through rates if pass-through of monetary policy rates behaved quite differently compared to regular times.

Second, my inertia proxies might not properly capture inertia but reflect heterogeneous preferences of consumers over different account attributes. If older accounts carry a different combination of attributes, this might affect demand even in absence of inertia. For example, internet accounts carry higher rates but also offer less service quality compared to regular accounts which a share of consumers might prefer over other combinations. While this argument cannot be fully invalidated, the evidence in Deuflhard, Georgarakos and Inderst (2017) showing that financial literacy strongly correlates with internet account usage and Deuflhard (2016) showing that inertia is lower for online banking users suggests a significant role of consumer choice frictions.

Third, accounts might have different marginal costs impacting pass-through from a supply-side perspective. For example, internet accounts are fully managed online by the depositor, while regular accounts include access to branch services. However, while these costs are partially variable, e.g., personel expenses at the branches, the bulk of them are incured for infrastructure and, thus, fixed at least in the medium run.

VII. Conclusion

In this paper, I analyze heterogeneous pass-through of monetary policy rates to retail bank rates using detailed panel data on variable-rate savings accounts in the Netherlands. I exploit variation in pass-through rates within banks to separate the effect of inertia from bank-level determinants. I find substantial heterogeneity in pass-through rates across banks but even account products offered by the same bank. Bank-specific factors explain around half of the variation in account-level long-run pass-through rates. Within banks, internet-managed and newer accounts capturing market segments with more flexible consumers exhibit substantially higher pass-through than regular and older accounts. This suggests inertia as an important source behind the impact of market power on pass-through as documented by prior studies. From a policy perspective, efforts to improve digitilization might have potentially surprising effects on the effectiveness of the monetary transmission channel.

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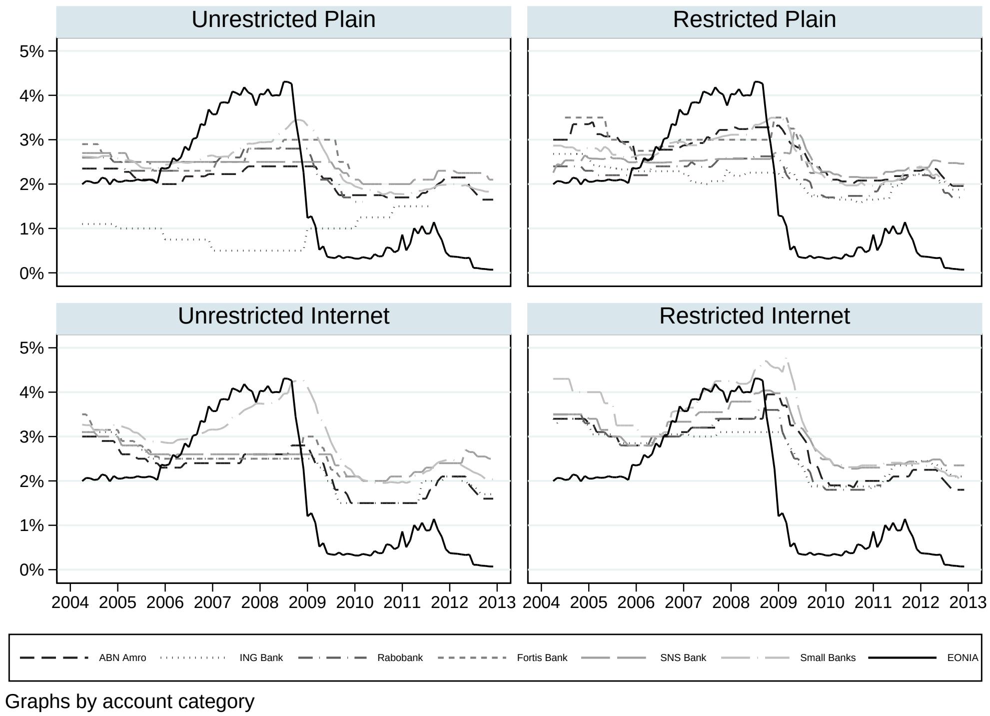

Figure 1. Interest rates and monetary policy

Note: The figure shows the evolution of average interest rates and the EONIA rate separately by account type.

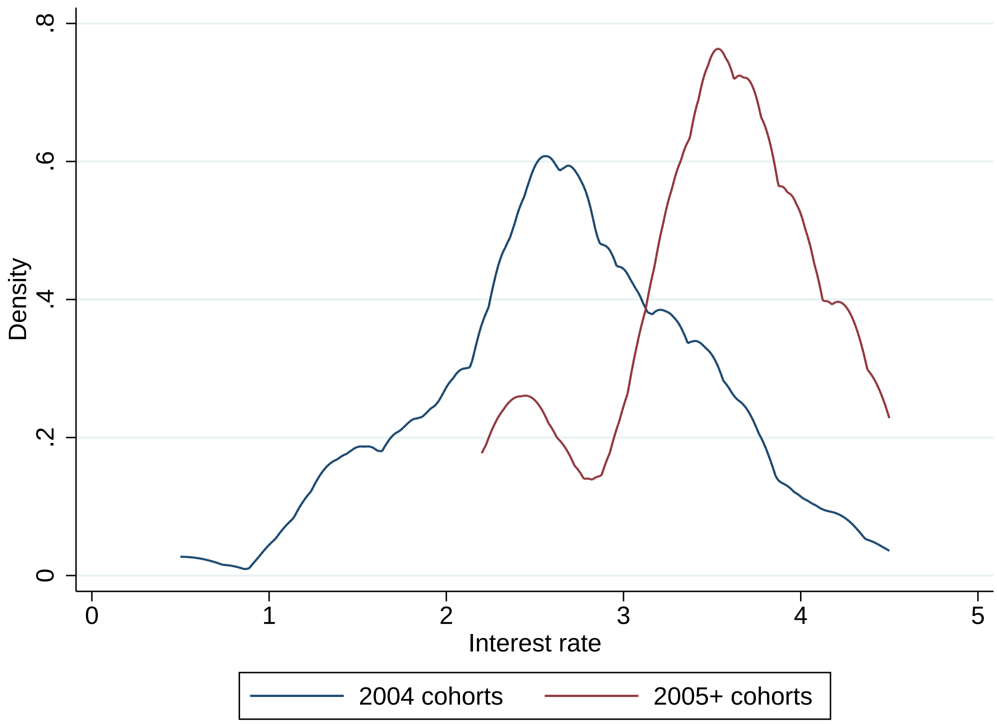

FIGURE 2. RATE DISTRIBUTION IN 2007 BY YEAR OF INTRODUCTION

Note: The figure shows the distribution of interest rates in 2007 separately for cohorts of accounts introduced in 2004 or earlier and cohorts introduced after 2004. Graphs for different years exhibit comparable patterns.

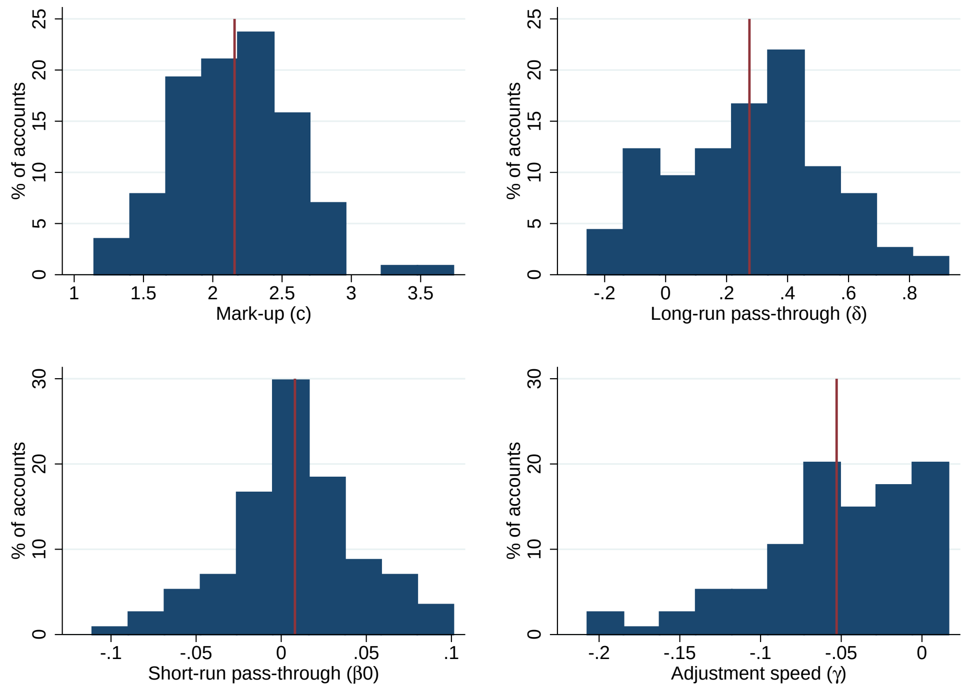

Figure 3. Distribution of parameter estimates

Note: The figure shows the distribution of the main parameters of interest from the random coefficient error correction model described in the main text. The red line indicates the weighted mean of the respective distribution.

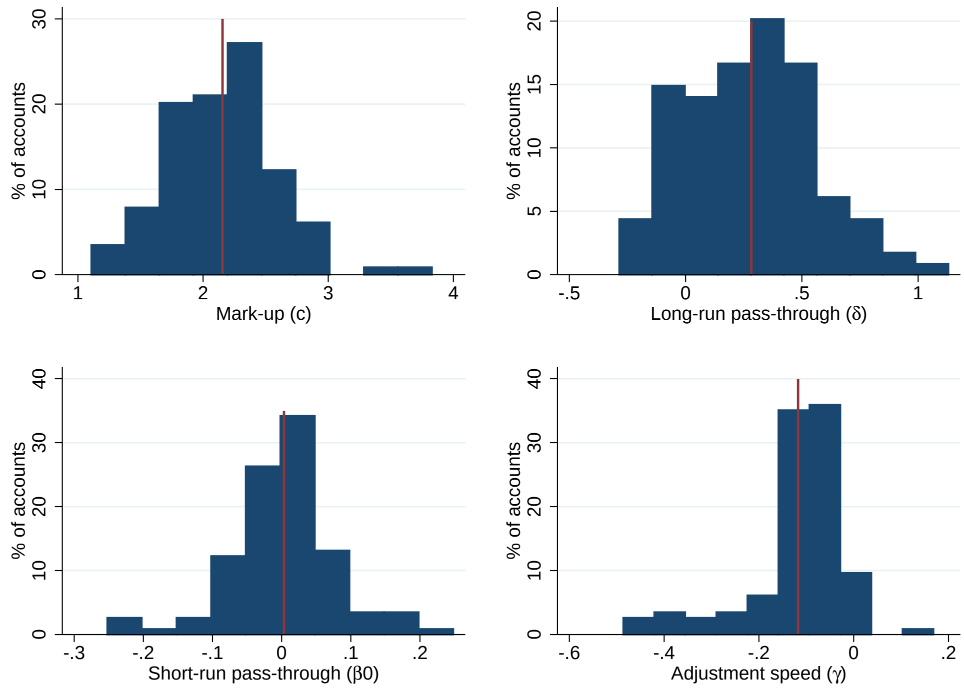

Figure 4. Distribution of parameter estimates

Note: The figure shows the distribution of the main parameters of interest from a series of error correction models estimated separately for each account. The red line indicates the mean of the respective distribution.

Table 1—Number of accounts by bank and account type

	Unrestricted Plain	Restricted Plain	Unrestricted Internet	Restricted Internet	Total
ABN Amro	2	5	1	2	10
ING Bank	1	7	1	2	11
Rabobank	1	4	0	1	6
Fortis Bank	1	1	1	0	3
SNS Bank	1	14	1	4	20
Small Banks	29	12	18	5	64
Total	35	43	22	14	114

Note: The table shows the number of accounts over the pooled sample by bank and account type for the largest five banks and the set of small banks.

Table 2—Interest rates by account age

	Model (1)		Model (2)		Model (3)	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Account age						
...1st year	-0.116***	0.027	-0.102***	0.028	-0.107***	0.024
...2nd year	-0.246***	0.038	-0.223***	0.037	-0.235***	0.035
...3rd year	-0.340***	0.057	-0.308***	0.053	-0.327***	0.052
...4th year	-0.442***	0.071	-0.401***	0.067	-0.435***	0.066
...5th year	-0.494***	0.073	-0.446***	0.07	-0.491***	0.071
...6th year	-0.514***	0.078	-0.464***	0.075	-0.516***	0.076
...7th year	-0.561***	0.087	-0.506***	0.082	-0.567***	0.085
...8th year	-0.592***	0.097	-0.533***	0.093	-0.606***	0.098
Constant	1.002***	0.03	0.926***	0.045	1.002***	0.056
N	9,360		9,360		9,360	
R-squared	0.32		0.38		0.43	
Time fixed effects	yes		yes		yes	
Account dummies	no		yes		yes	
Bank fixed effects	no		no		yes	

Note: The table shows the results from a regression of log monthly premiums on various controls. Account dummies contain separate dummies for each of the four account categories. Standard errors are clustered at the account level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3—Model estimates and robustness

	Primary specification		Robust (1)		Robust (2)	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Δ Eonia (t)	0.005	0.009	0.005	0.007	0.010	0.013
Δ Eonia (t-1)	-0.016	0.011	-0.001	0.008	0.011	0.009
Δ Eonia (t-2)	-0.012	0.012	-0.004	0.009	-0.011	0.012
Δ Eonia (t-3)	0.024**	0.012	0.035***	0.013	0.046***	0.014
Δ Eonia (t-4)	0.040***	0.014	0.054***	0.014	0.076***	0.025
Δ Eonia (t-5)	0.035***	0.011	0.055***	0.010	0.033*	0.017
Δ Eonia (t-6)	0.052***	0.013	0.078***	0.012	0.078***	0.021
Cointegration term	-0.064***	0.011	-0.025***	0.003	-0.026***	0.004
Constant	-0.016***	0.005	-0.011***	0.001	-0.006**	0.002
Mark-up	2.157***		2.142***		1.974***	
Long-run pass-through	0.275***		0.220***		0.263***	
N	8,562		8,562		3,332	
Adjusted R-squared	-		0.10		0.11	
Cointegration test	-3.47					
Heterogeneity test	4076.82					

Note: The table shows the estimates from several pass-through specifications. Primary specification shows the results described in equations (1) and (2). Robust (1) shows the same specification without allowing for heterogeneity. Robust (2) restricts the sample to a balanced panel. Standard errors are clustered at the account level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4—Pass-through determinants

	Long-run (1)		Long-run (2)		Mark-up (1)		Mark-up (2)	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Internet account			0.153***	0.039			0.073	0.076
Introduction after 2004 (years)			0.079***	0.017			0.069***	0.026
Constant	0.294***	0.082	0.066	0.059	2.035***	0.091	1.853***	0.131
Bank Fixed effects	yes		yes		yes		yes	
N	114		114		114		114	
R-squared	0.55		0.74		0.40		0.44	

Note: The table shows the estimates from equation (3) described in the main text. Long-run (1) and Mark-up (1) include only bank fixed effects as controls. Long-run (2) and Mark-up (2) add additional account-level controls. Standard errors are robust to heteroscedasticity. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix A: Swamy Random Coefficient Model

Following Swamy (1970), consider a random-coefficients model of the form:

$$y_{it} = X_{it}\beta_i + \epsilon_{it} \tag{A1}$$

where $i = 1, .., n$ denotes cross-sectional units and $t = 1, .., T$ denotes time. X_{it} denotes a matrix of covariates and β_i is a vector of parameters. Each β_i is related to an underlying common parameter vector β as follows:

$$\beta_i = \beta + v_i \tag{A2}$$

with $E[v_i] = 0$, $E[v_i v_i'] = \Omega$, $E[v_i v_j'] = 0$ for $j \neq i$, and $E[v_i \epsilon'] = 0$ for all i and j. Combining (A1) and (A2) yields:

$$y_{it} = X_{it}(\beta + v_i) + \epsilon_{it} = X_{it}\beta + u_{it} \tag{A3}$$

with $u_{it} = X_{it}v_i + \epsilon_{it}$. We can now stack the equations for all panels and time periods as follows:

$$y = X\beta + u \tag{A4}$$

where

$$\Pi = E[uu'] = \begin{bmatrix} \Pi_1 & 0 & ... & 0 \\ 0 & \Pi_2 & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \Pi_n \end{bmatrix} \tag{A5}$$

and $E[u_i u_i'] = \Pi_i$. Estimating the parameters of equation (A4) is a standard problem in generalized least squares (GLS), so

$$\begin{aligned}\hat{\beta} &= (X'\Pi^{-1}X)^{-1}X'\Pi^{-1}y &\text{(A6)}\\ &= (\sum_i X_i'\Pi_i^{-1}X_i)^{-1}\sum_i X_i'\Pi_i^{-1}y_i &\text{(A7)}\\ &= \sum_i \omega_i b_i &\text{(A8)}\end{aligned}$$

where $\omega_i = [\sum_j[\Sigma + \sigma_{jj}(X_j'X_j)^{-1}]^{-1}]^{-1}[\Sigma + \sigma_{ii}(X_i'X_i)^{-1}]^{-1}$ and $b_i = (X_i'X_i)^{-1}X_iy_i$ showing that $\hat{\beta}$ is a weighted average of the panel-specific OLS estimates. The variance of $\hat{\beta}$ is:

$$Var(\hat{\beta}) = (X'\Pi^{-1}X)^{-1} = \sum_i[\Sigma + \sigma_{ii}(X_i'X_i)^{-1}]^{-1} \tag{A9}$$

In addition, one often wishes to obtain estimates of the panel-specific β_i vectors as well. As discussed by Judge et al. (1982), if attention is restricted to the class of estimators β_i^* for which $E[\beta_i^*|\beta_i]$, then the panel-specific OLS estimator b_i is appropriate. However, if one does not condition on β_i, then the best linear unbiased predictor is:

$$\hat{\beta}_i = \hat{\beta} + \Sigma X_i'(X_i\Sigma X_i' + \sigma_{ii}I)^{-1}(y_i - X_i\hat{\beta}) \tag{A10}$$

Greene (2003) suggests using the following method to obtain the variance of $\hat{\beta}_i$. Define $A_i = (\Sigma^{-1} + \sigma_{ii}^{-1}X_i'X_i)^{-1}\Sigma^{-1}$. Then:

$$\hat{\beta}_i = [A_i(I - A_i)]\begin{bmatrix}\hat{\beta}_i\\ b_i\end{bmatrix} \tag{A11}$$

and:

$$Var(\hat{\beta}_i) = [A_i(I - A_i)]Var\begin{bmatrix}\hat{\beta}_i\\ b_i\end{bmatrix}\begin{bmatrix}A_i'\\ (I - A_i)'\end{bmatrix} \tag{A12}$$

The GLS estimator is both consistent and efficient and, while inefficient, b_i is nevertheless also a consistent estimator of β. Swamy (1970) showed that a consistent estimator of Σ is given by:

$$\hat{\Sigma} = \frac{1}{n-1}(\sum_{i=1}^{n} b_i b_i' - n\bar{b}\bar{b}') - \frac{1}{n}\sum_{i=1}^{n}\hat{\sigma_{ii}}(X_i'X_i)^{-1} \tag{A13}$$