Paying for the prices: the cost of taming inflation

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July 15, 2024

[PRELIMINARY DRAFT: please do not quote or redistribute]

Abstract

Using high-frequency data on individual bank accounts transactions and card payments, we investigate the impact of monetary policy on consumption at daily frequency, and we focus on the magnitude and the transmission dynamics of interest rate shocks. The granularity of the data allows us to build consumption series segmented by age, gender, education level, and region to explore asymmetric features of monetary policy transmission. A parsimonious local projection specification allows us to flexibly include a variety of controls, to explore the consumption effects of the full maturity profile of the yield curve, and to disentangle extensive and intensive margins contribution. Furthermore, a nonlinear extension of our framework is able to identify the effects of positive and negative monetary policy shocks. A selection of our findings includes: (a) household spending reaction peaks approximately eleven months after the initial shock, mainly driven by the extensive margin; (b) negative shocks are definitely contractionary, while positive shocks are unable to show a decisive expansionary effect; (c) interest rate shocks from the short and medium-term maturities of the yield curve do not present significant differences in the way in which they affect consumption, while longer term maturities have a quicker transmission to household spending, consistent with the Slovak real estate market structure; (d) monetary policy is symmetric in its effects and transmission timing across the demographic dimensions of age, sex, education, and region.

Keywords: Consumption; Monetary policy; Pass-through; high-frequency; nonlinear; granular data
JEL Classification: E52;E61;C32;C51;C81

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1 Introduction

This draft illustrates an initial effort to assess the transmission mechanism of monetary policy shocks to household consumption. Our investigation is grounded in a large and rich literature that typically relies on low-frequency macro-data released from statistical agencies Christiano et al. (1999). Making use of a novel database of daily household bank transactions, we estimate both the magnitude and timing of policy surprises on consumer spending. Our findings reveal a lagged transmission of approximately ten months, mainly driven by the extensive margin. Further, we investigate asymmetries in both size, timing, and evolution between positive and negative interest rate shocks.

Our empirical findings on the effects of positive and negative monetary policy surprises align with recent research based on US data (Tenreyro & Thwaites 2016, Angrist et al. 2018, Barnichon & Matthes 2018), and advocate for active monetary support during economic downturns. Our work contributes new insights into the relative effectiveness of conventional versus unconventional monetary tools, a field of the literature so far focused on financial markets, given the lack of high-frequency macroeconomic data (Gürkaynak et al. 2005, Vissing-Jorgensen & Krishnamurthy 2011, Gilchrist et al. 2015, Gagnon et al. 2011, Swanson 2017).

The availability of high-frequency data has mostly been confined to financial markets, with the majority of the studies focused on the impact of policy announcements on financial markets (Kuttner 2001, Cochrane & Piazzesi 2002, Bernanke & Kuttner 2005, Gürkaynak et al. 2005, Hanson & Stein 2015, Gilchrist et al. 2015, Nakamura & Steinsson 2018). Yet, a growing body of research, pioneered by Bagliano & Favero (1999), is exploring the opposite direction of shock transmission using high-frequency information from financial markets to improve the identification of monetary policy shocks -often in a VAR setting (Gertler & Karadi 2015, Jarociński & Karadi 2020, Miranda-Agrippino & Ricco 2021, Andrade & Ferroni 2021). The latest contribution by Sandri & Grigoli (2022) couples high-frequency spending series to the renowned database of monetary events compiled by Altavilla et al. (2019), offering a foundation upon which our study builds.

The increasing availability of large high-frequency databases of macroeconomic variables has enriched economic research. In particular, the diffusion of electronic payments and the vast amount of information collected by private firms and government bodies has transformative potential in the economic profession Einav & Levin (2014). During the Covid crisis card payment data have known a sudden popularity for their ability to capture in real time change in consumption habits and dynamics across specific classes of goods and services (Andersen et al. 2020, Bounie et al. 2020, Chetty et al. 2020, Hacıoğlu-Hoke et al. 2021), when unemployment spells hit ((Ganong & Noel 2019, Andersen et al. 2023), or when the extensive margin of demand changes (Einav et al. 2021).

Using higher frequency macroeconomic series has the potential to redefine the interpretation of economic phenomena. Paccagnini & Parla (2023) show on US data how the same shock to financial conditions is read differently by models, as an aggregate supply or demand shock depending on the frequency of the data used. Our use of daily frequency allows for a more precise identification of the transmission lags of monetary policy, as well as for a cleared differentiation of shock transmission when shocks hits different segment of yield curve profile.

The paper develops as it follows. Section 2 describe the data, Section 3 presents our empirical approach and results, and Section 4 concludes.

2 Data description

Our analysis is based on a confidential dataset of bank transactions of Slovak household accounts across multiple institutions. The dataset covers the period from January 2019 to December 2022 and includes details such as the amount and nature (i.e., card or wire transfer) of each transaction, as well as its merchant classification. We also have access to contemporaneous characteristics of each account, including age, gender, education level, and region.

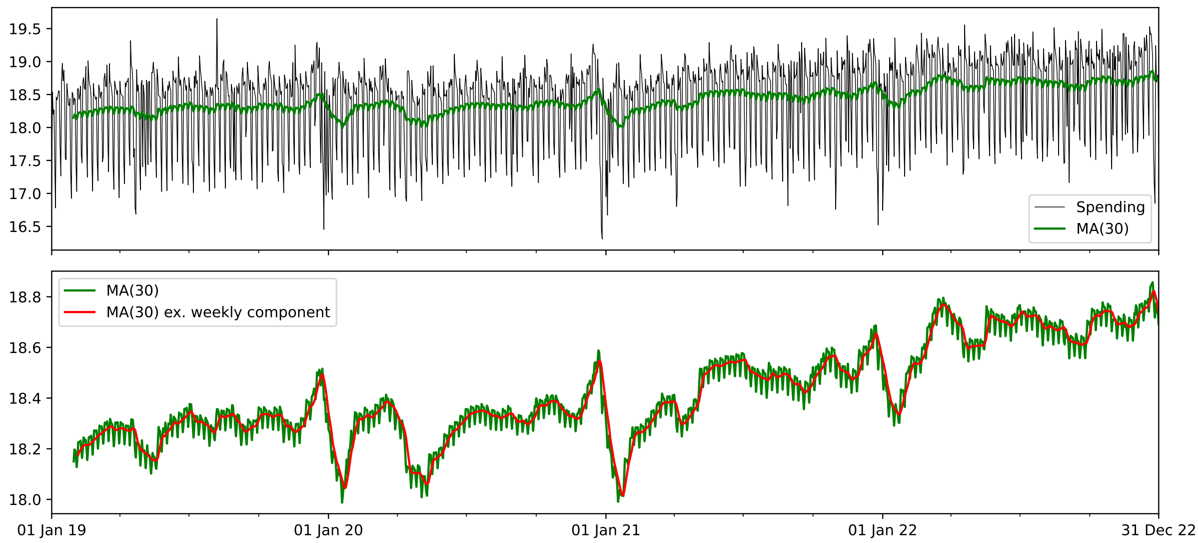
Furthermore, the classifying taxonomy is not homogeneous across the banks, making it difficult to generate coherent subdivisions of the transactions. In a first instance, we proceed with a three step approach: (a) We filter out all positive transactions; (b) We exclude some of the categories which do not enter consumption (i.e., loan repayments, cancelled incoming payments, investments, fines, court-mandated repayments, and taxes); (c) we sum the remainders by day to create a daily spending series that could act as a high-frequency consumption proxy. Table 1 the correlation between our daily spending series and private consumption data sourced from national accounts. Figure 1 shows the spending proxy at daily frequency.

Table 1: Correlation between our Spending variable and quarterly consumption from National Accounts

	Levels	**QoQ**	**YoY**
Correlation	97.3%	84.8%	87.1%

Source: NBS and Eurostat.
Note: Correlation with Eurostat National Accounts private consumption of Households in levels and growth rates, quarter-on-quarter and year-on-year. Spending is calculated summing all negative transactions excluding irrelevant categories.

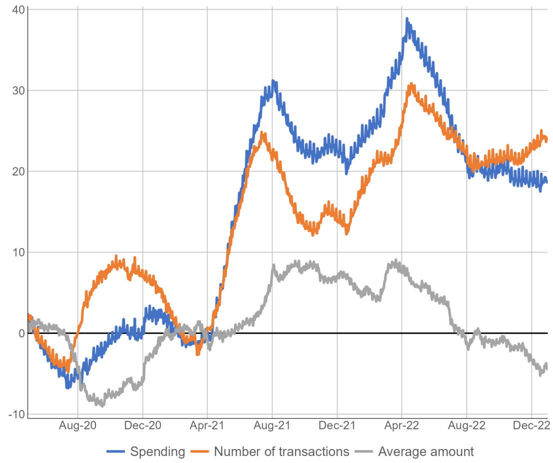
Figure 1: Spending proxy



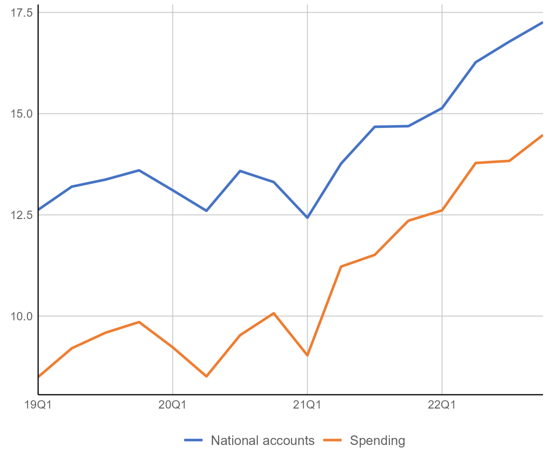
Source: NBS calculations.
Note: Spending proxy. Panel above shows the daily log-value of the spending proxy and its MA(30) smoothing. Panel below further filters out the weekly component.

Figure 2 illustrates some key descriptive features of the data. Since this granularity of spending tends to be volatile across days of the week and of the month, public holidays, and idiosyncratic events, we smooth our spending, intensive, and extensive margin indicator with a 120 days moving average and present year over year growth rates as in Chetty et al. (2020). Panel 2a shows a steep increase in the number of transactions in the second quarter of 2021, which drove the total spending and is the source behind the convergence in level shown in 2b. Our expenditures are clearly bimodal 2c, with two peaks at around 43 and 130 million. This stems from a clear difference in spending behavior across days shown in panel 2d, with the weekend combined averaging about 60% of the average expenditure of any other day.[1]

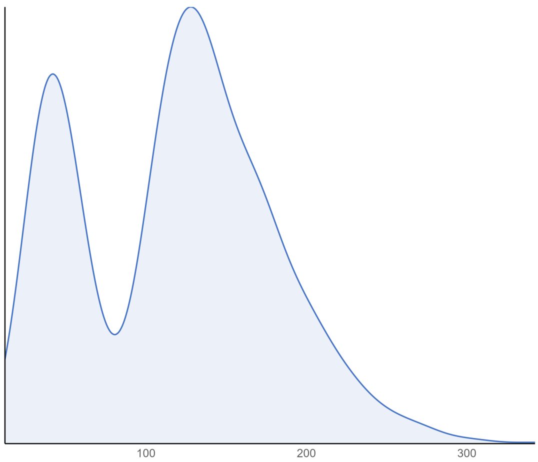
Figure 2: Descriptive charts about the spending proxy of consumption



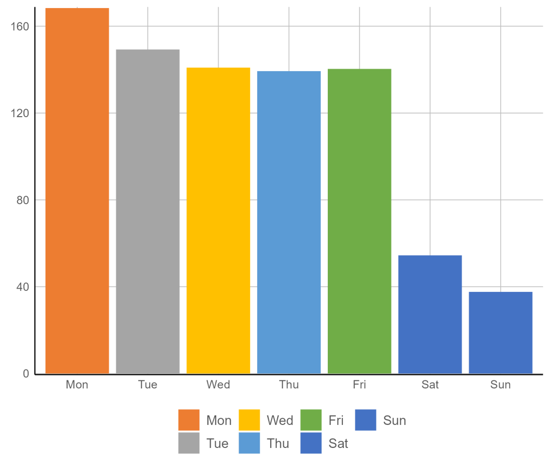
(a) Year-on-year growth rates (percentages)



(b) Spending and national accounts data (EUR billions)



(c) Frequency of daily spending (EUR millions)



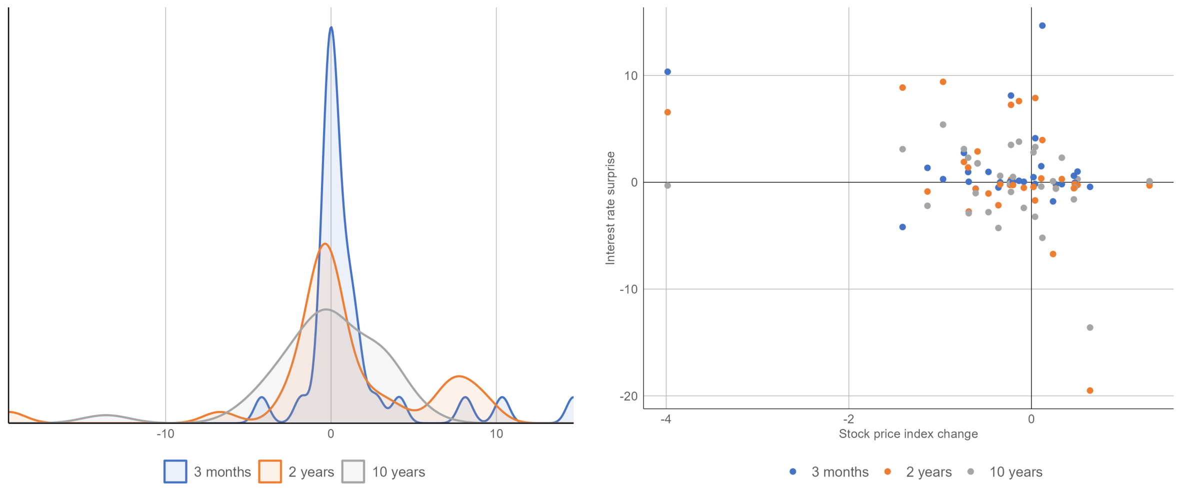
(d) Weekdays average spending (EUR millions)

Source: NBS and Eurostat.
Notes: Various descriptive charts about the spending proxy of consumption. Panel 2a shows annual growth rates at daily frequency. Extensive and intensive margins are represented by the number of transactions and the average amount per transaction, respectively. All variables are year-on-year percent change of the 120-day moving average. Panel 2b shows spending data aggregated at quarterly frequency, in levels, compared with private consumption from National Accounts data. Panel 2c shows the kernel distribution of the spending per day. Panel 2d complements the previous panel, with average spending per days of the week.

[1] We are aware that this difference in behavior may originate from a technical feature of the system, registering weekend transactions on a different day.

We couple our daily spending proxy of consumption with daily interest rate and stock market surprises from the EA-MPD database of Altavilla et al. (2019). Specifically, we focus on Overnight Index Swap (henceforth OIS) rates surprises at 2-year maturity to capture the influence of forward guidance as in (Gilchrist et al. 2015, Hanson & Stein 2015). We consider the full event window (from the pre-release of monetary policy decision to after the press-conference) surrounding monetary policy announcements, as we assume that household consumption is more directly impacted by the monetary decision itself rather than the specificities and details of its communication flow. To disentangle the information bundle in monetary policy events, we follow Cieslak & Schrimpf (2019) as well as Jarociński & Karadi (2020) and use information about the Euro STOXX50 index. Figure 3 illustrates the distributions of interest rate surprises for different maturities.

Figure 3: Interest shocks and stock prices around ECB monetary events



(a) Frequency of shocks at maturities (basis points)

(b) Interest rate surprises and stock prices

Source: NBS calculations, EA-MPD database.
Note: Panel 3a summarizes the change in interest rate for different maturities around monetary policy events, in basis points. Panel 3b shows the interest rate surprises (in basis points) against the concomitant Euro STOXX50 index change (in percentage points).

3 Empirical evidence

To explore the effect of interest rate shocks on spending, we follow Sandri & Grigoli (2022) and set up a local projection specification, á la Jordà (2005). The shock identification relies on the fundamental assumption that, in Slovakia, monetary policy shocks are entirely exogenous, other than assuming that rate changes in a narrow window around the monetary policy events are driven solely by the policy surprise, as in Kuttner (2001), Cochrane & Piazzesi (2002). We also use stock prices as a control to disentangle the informative content about the state of the economy.

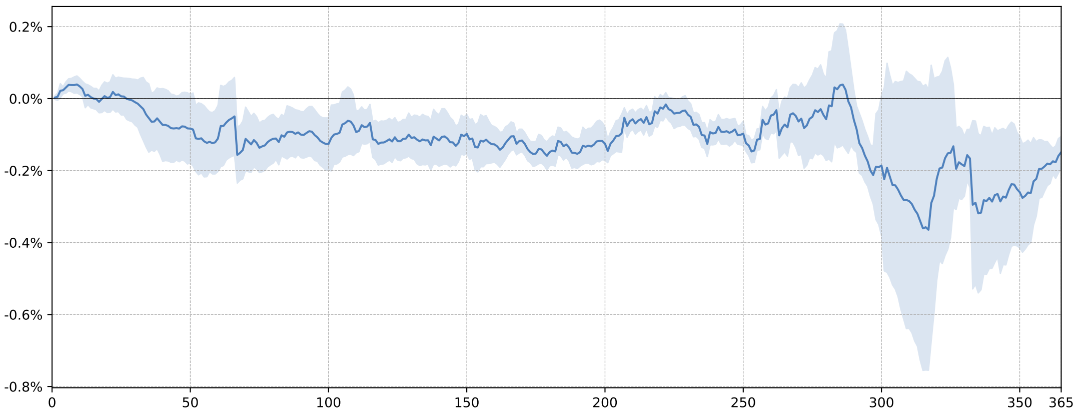
3.1 Baseline specification

In our baseline econometric specification, we target the cumulative response of spending to an interest rate shock at horizon h. The model is as follows:

$$S_{t+h}S_{t-1} = \alpha^h + \sum_{p=1}^{\overline{p}} \beta_p^h I_{t-p} + \sum_{p=1}^{\overline{p}} \gamma_p^h cases_{t-p} + \sum_{p=1}^{\overline{p}} \phi_p^h deaths_{t-p} + \sum_{p=1}^{\overline{p}} \theta_p^h support_{t-p} + \sum_{p=1}^{\overline{p}} \rho_p^h s_{t-p} + dow^h + doy^h + \varepsilon_t^h \tag{1}$$

Where S_t represents the log of our spending proxy at time t, over a horizon $h = 0, \ldots, 365$. I is the interest rate shock, externally identified and drawn from the EA-MPD database. The array of controls variables includes Covid-19 related variables, since most of our sample falls inside pandemic period, as well as calendar control variables: day of the week, as well as day of the year, effects, in addition to the number of cases and deaths from pandemic, to capture any fear-induced consumption reduction. We also control for the government income support scheme during the pandemic scheme, and control for the persistence of the dependent variable using the year-on-year log difference of spending, s. All control variables have seven lags ($\overline{p} = 7$), and ε is a robust standard Newey & West (1987) error with finite sample adjustments.
Figure 4 shows the response of spending to a 100 basis points interest rate shock to 2-year OIS, as per our Equation 1. Spending declines fast to about 0.1%, before peaking about ten months after the shock. The partial recovery looks slow, taking the remaining part of the year.

Figure 4: Spending response to an interest rate shock – Baseline specification



Source: NBS calculations, EA-MPD database.
Note: Spending response to a 100 basis points shock to the 2-year OIS interest rates. Regression includes calendar (day of the week, day of the year), as well as pandemic controls (cases, deaths, and government support). Shaded area represents 90% confidence band.

3.2 Extended set of controls and specification

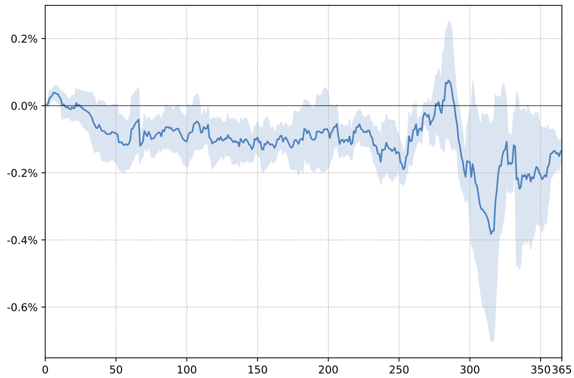
We augment our specification including controls for inflation and stock prices. We include expected, perceived, and realized inflation to account for forward-looking spending behavior, as well as for wealth effects triggered by the present inflation perception as well. The stock price index -entering the specification both independently and in interaction with interest rate surprises- helps to untangle the information contained in a single monetary event. To further understand the source of the dynamics, we run the same model using as dependent variable the number of transactions and their average amount. We interpret those results as a measure of, respectively, the extensive and intensive margin contribution. The augmented specification now becomes:

$$\begin{aligned}\{S_{t+h}S_{t-1}, N_{t+h} - N_{t-1}, M_{t+h} - M_{t-1}\} = \\ \alpha^h + \sum_{p=1}^{\overline{p}} \beta_p^h I_{t-p} + \sum_{p=1}^{\overline{p}} \gamma_p^h cases_{t-p} + \sum_{p=1}^{\overline{p}} \phi_p^h deaths_{t-p} + \sum_{p=1}^{\overline{p}} \theta_p^h support_{t-p} + \\ \sum_{p=1}^{\overline{p}} \delta_p^h \pi_{t-p} + \sum_{p=1}^{\overline{p}} \lambda_p^h \pi_{t-p}^E + \sum_{p=1}^{\overline{p}} \tau_p^h \pi_{t-p}^P + \\ \sum_{p=1}^{\overline{p}} \xi_p^h I_{t-p} \times SP_{t-p} + \sum_{p=1}^{\overline{p}} \eta_p^h SP_{t-p} + \sum_{p=1}^{\overline{p}} \rho_p^h s_{t-p} + \\ dow^h + doy^h + \varepsilon_t^h \end{aligned} \quad (2)$$

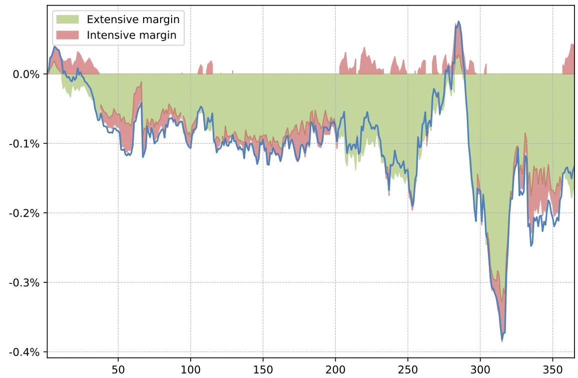
The dependent variable of Equation 2 is, alternatively, the spending proxy, the volume of transactions, or the average value per transaction. SP denotes the innovation concomitant innovation in stock prices to the interest rate shocks. The inflation controls articulate in Expected inflation (π^E), Perceived inflation (π^P), and realized inflation (π).

The spending response to a 100 bp shock is, as shown in panel 5a, consistent with the results from the baseline specification. The short-term effect of the shock on spending is now slightly more pronounced, peaking after about ten months. As shown in panel 5b, the response appears mainly driven by a reduction in the volume of transactions, with not much contribution from the intensive margin.

Figure 5: Spending response to an interest rate shock – Extended controls and specification



(a) Spending response



(b) Intensive vs Extensive margin decomposition

Source: NBS calculations, EA-MPD database.
Note: Panel 5a show the Spending response to a 100 basis points interest rate shock to 2-year OIS rates. Regression includes calendar (day of the week, day of the year), pandemic (cases, deaths, and government support), inflation (perceived, expected, and realized), and stock price controls. Shaded area represents 90% confidence band. Panel 5b presents the decomposition of the point estimated response between intensive and extensive margin. Margins are the number of transactions and their average amount, respectively.

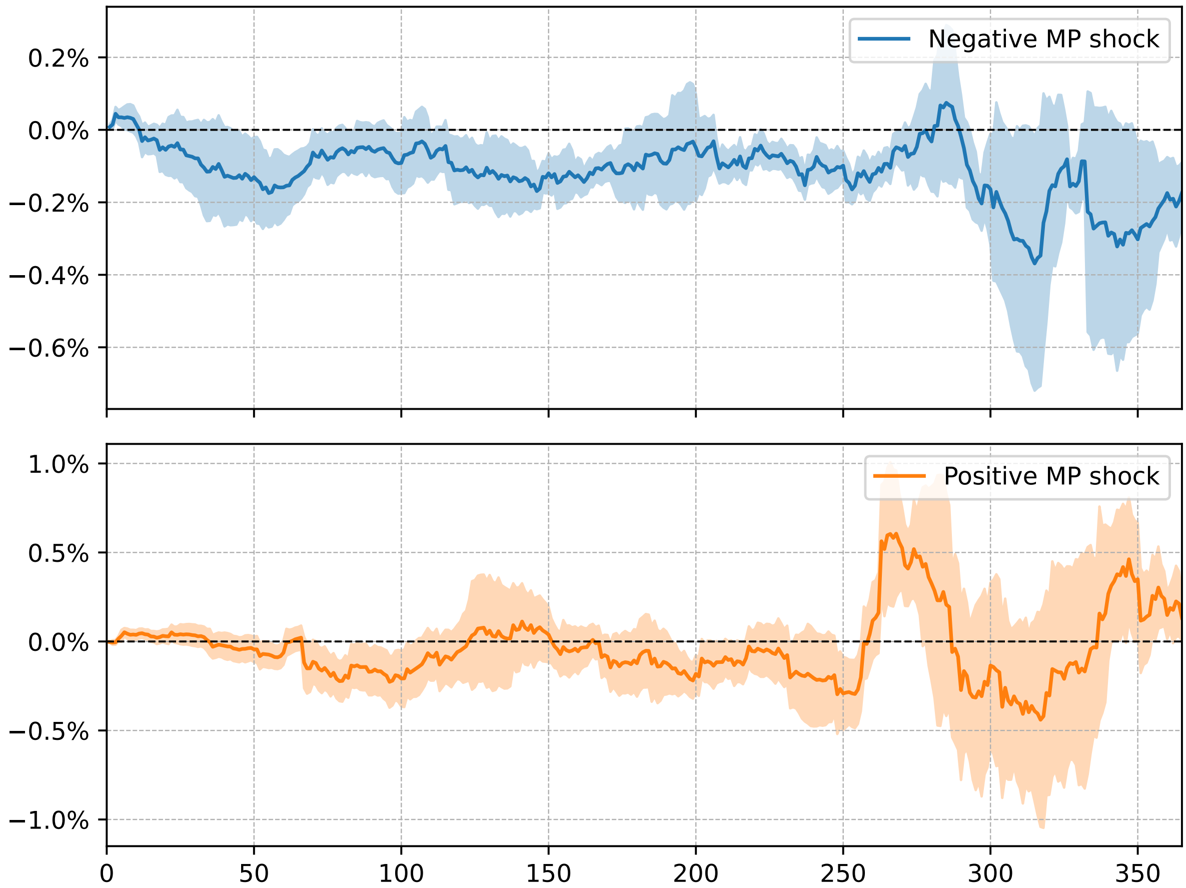
3.3 The asymmetric effect of monetary policy: positive and negative shocks

To assess any asymmetry between positive and negative interest rate shock effect, we compute state probabilities using a logistic function as proposed by Auerbach & Gorodnichenko (2012):

$$F(z_t) = \frac{e^{(-\gamma z_t)}}{\left(1 + e^{(-\gamma z_t)}\right)} \tag{3}$$

Where z_t is generated as a dummy sign function from the interest rate surprise series. We calibrate γ to allow sharp transitions across states. This methodology let us to save degrees of freedom compared to simply multiplying everything by a binary dummy variable, while allowing, in principle, to test for a smoother transition process to accommodate for a slight persistence (either backward or forward looking) of the shock. Nonlinear impulse response functions are computed as in Ahmed & Cassou (2016).
Figure 6 questions the long-term effectiveness of negative interest rate surprises, a positive monetary policy shock, in stimulating consumption. Overall, after a first period of small to none statistical significance, the spending reaction veers to the positive territory around 9 months from the shock. The increase, is, however, short lived and the longer term effect seems muted.
On the other hand, a positive interest rate variation –a negative MP shock– depresses spending and again peaks after about ten months. The shock yield is comparable in magnitude to the linear specification of Equation 2.

Figure 6: Spending response to an interest rate shock – Positive and negative shocks



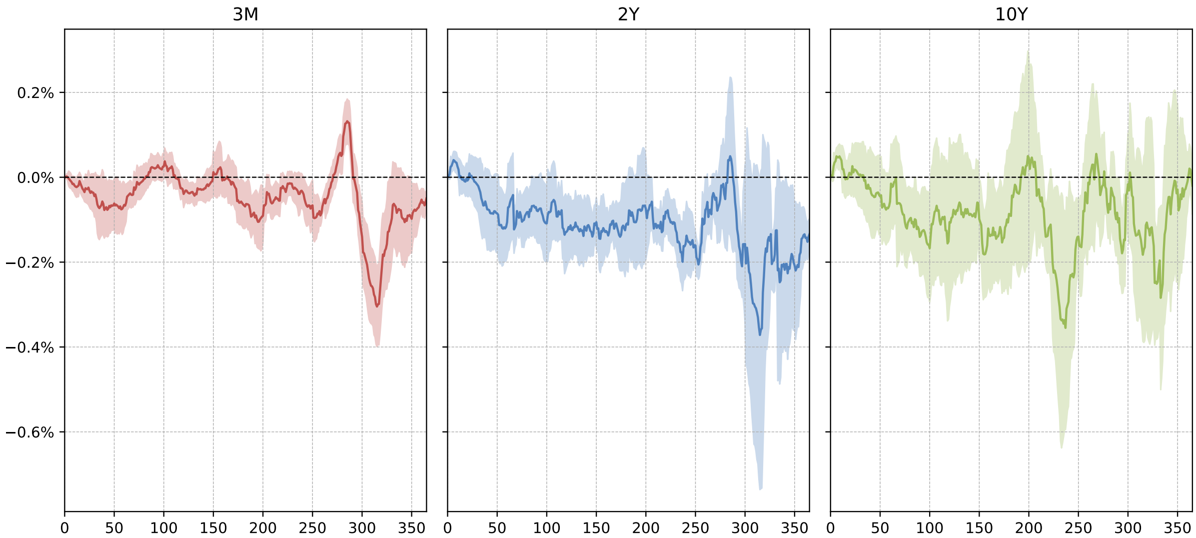
Source: NBS calculations, EA-MPD database.
Note: Spending response to a 100 basis points interest rate shock to 2-year OIS rates, by sign of the shock. Regression includes calendar (day of the week, day of the year), pandemic (cases, deaths, and government support), inflation (perceived, expected, and realized), and stock price controls. Shaded area represents 90% confidence band. Positive and negative shock responses are differentiated using a logistic function fed with a normalized series of shocks.

3.4 Horizons of monetary policy

Our econometric framework allows us to examine possible differences in the speed of transmission of monetary policy depending on the specific segment of the yield curve affected by the policy. This exercise directly feeds into the debate around whether conventional interest rate policy (tending to affect shorter-term rates) or unconventional policy tools (operating at longer maturities) have more effect. We augment our specification with 3-month and 10-year maturity OIS rates surprises around monetary events.

Figure 7 details the transmission to spending of the three different maturities to pick up short, long, and medium term. Each maturity includes the other two as controls. The first striking result is that the dynamics of the spending response for a 2-year shock stay the same when controlling for longer and shorter maturities. The shock to the 3-month maturity yields a similar spending evolution to the 2-year maturity, peaking after the tenth month. The ten years maturity horizon captures, for Slovakia, the evolution of real estate market since it is tied to residential mortgages and peaks faster than the shorter one, signaling a more direct channel of transmission to household spending. Overall, conventional monetary instruments appear to be extremely effective in cooling the Slovak demand, with longer maturities acting quicker.

Figure 7: Spending response to interest rate shocks at different maturities



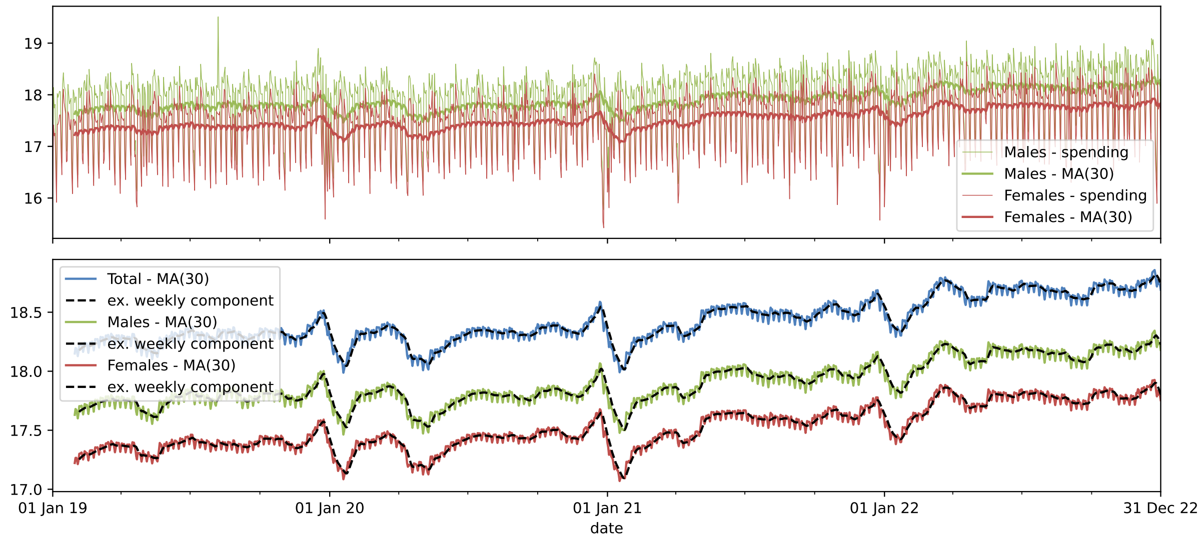
Source: NBS calculations, EA-MPD database.
Note: Spending response to a 100 basis points interest rate shock to various OIS maturities. Regression includes calendar (day of the week, day of the year), as well as pandemic controls (cases, deaths, and government support). Shaded area represents 90% confidence band. Each maturity controls for the others.

3.5 Missing asymmetries

We control whether a monetary policy surprise has a different effect on spending proxies across the main demographic categories of our sample: gender of the account holder, and geographical region of permanent residence.

Gender is, in our database, a binary option: either male or female. Since we do not possess any information about the composition of households, we are unable to group accounts together, thus missing entirely on the within-household dimension of the spending decision. Since it is reasonable to assume that the bulk of expenditures in a household are negotiated and agreed upon, being this could bring closer the spending behavior originating from male and female account holders. Furthermore, we only know the first owner of each account, thus making joined accounts invisible. Figure 8 shows the different proxies computed for spending originating from male and female-owned bank accounts, before and after smoothing them with a MA(30). Male-generated consumption sums up to about 60% of the total.

Figure 8: Spending proxy computed by gender



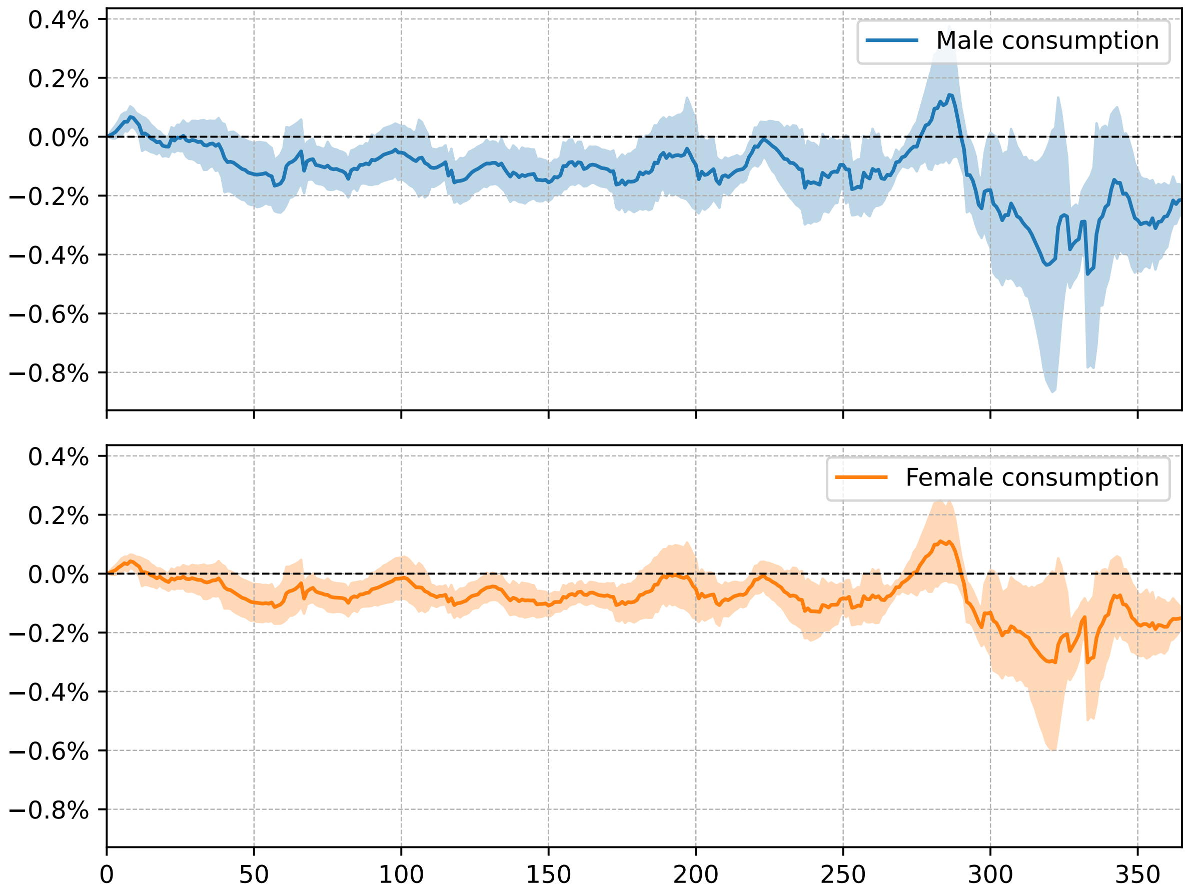
Source: NBS calculations, EA-MPD database.
Note: Spending proxy by gender and total. Panel above shows the daily log-value of the spending proxies and their MA(30) smoothing. Panel below highlights the weekly component still present in the MA(30) smoothing for all the proxies.

The region of permanent residence comes, on the other hand, with some caveat. First, the geographical details is on NUTS3 level, leaving us with eight subdivisions of the country. Second, we do not possess continuous demographic information for the duration of our sample, and we rather have a snapshot of customers personal characteristics taken at the end of our sample period, 31/12/2022.

That is to say that we have no way to track any change of residence within the two years of our sample, and that we have no way to distinguish a urban versus periphery change of residence inside the same region. Furthermore, the permanent residence recorded in the our database is an administrative concept not necessarily coinciding with the actual place of residence. All these factors concur to blur the picture when trying to pick up any signal of regional heterogeneity.

Figure 9 shows a substantial consistency of shock yields between male and female account holders, with some difference in the magnitude of the peak response to the shock, smaller for females. Considering that male and female-generated spending is not equally sized, with male-owned accounts being responsible for about 60% of the whole, the two yields peak around -0.24% and -0.15% of the total spending.

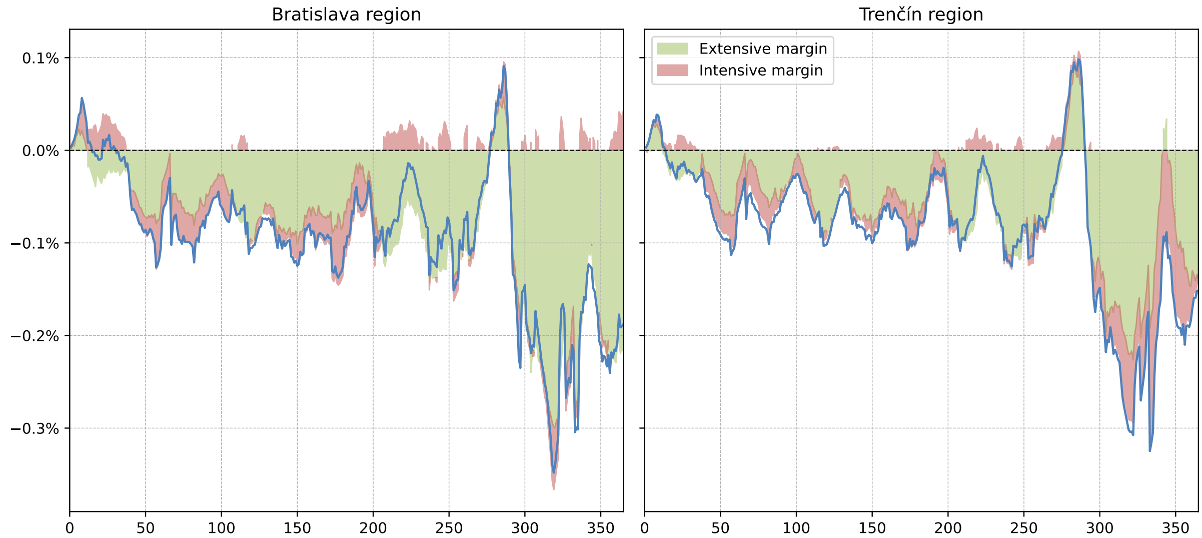
Figure 9: Spending response to an interest rate shock – Gender asymmetries



Source: NBS calculations, EA-MPD database.
Note: Differences in gender spending in response to a 100 basis points interest rate shock to 2-year OIS rates. Regression includes calendar (day of the week, day of the year), pandemic (cases, deaths, and government support), inflation (perceived, expected, and realized), and stock price controls. Shaded area represents 90% confidence band. Positive and negative shock responses are differentiated using a logistic function fed with a normalized series of shocks.

Slovakia has eight NUTS3-level subdivisions. Figure 10 shows only two of them, the most strikingly different: the district of the capital and Trenn, a large district in the north of the country. Despite differences being more marked than those between genders, the general message is broadly consistent: a peak reaction after ten months, mainly driven by extensive margin. The different degree of contribution of the average value of a transaction, the intensive margin, is the most relevant difference between the two regions.

Figure 10: Spending response to an interest rate shock – Geographical asymmetries



Source: NBS calculations, EA-MPD database.
Note: Spending response to a 100 basis points interest rate shock to 2-year OIS rates in two of the eight Slovak regions. Regression includes calendar (day of the week, day of the year), pandemic (cases, deaths, and government support), inflation (perceived, expected, and realized), and stock price controls. Shaded area represents 90% confidence band. Positive and negative shock responses are differentiated using a logistic function fed with a normalized series of shocks.

4 Conclusion

This study represents an initial effort to assess the features of the transmission mechanism of monetary policy shocks to household consumption in Slovakia. Making use of a novel daily database of transactions from household bank accounts, we estimate the magnitude and timing of the influence of policy surprises on consumer spending. We find a lagged transmission of about ten to eleven months, mainly driven by the extensive margin. Shocks recover is delayed, with a slow climb to a negative effect of spending of about -0.2% after a 100 basis points shock. Further analysis reveals that while negative shocks have a definitively contractionary effect, positive shocks are only weakly expansionary —though they do influence consumption more rapidly. Shock delivered through shorter and medium-term maturities have a similar dynamic and evolution. Medium term maturities, capturing unconventional monetary policy, yield a lower long-term effect on spending, where spending shocked through shorter term maturities bounces back quicker. Longer term maturities, strongly tied to the real estate market dynamics, transmit the shock to spending faster, albeit with the same magnitude, and also recover within the year horizon.

Our analysis find more similarity than differences in the effects of monetary policy across regions and genders. This could be due to some confounding factors, the inability to track movements across regions or identify households, blurring the differences and making harder to highlight regional and gender idiosyncrasies.

Future research is needed to explore the potential asymmetric effects of shocks across demographic characteristics, income ranges, geographic location, and consumption category.

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