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## Abstract

We analyze the impact of monetary policy on consumer spending using credit card data. Because of their high frequency, these data improve identification and allow for a precise characterization of the transmission lags. We find that shocks to short-term interest rates affect spending much more rapidly than shocks to longer-term interest rates. We also detect significant asymmetries. While interest rate rises are contractionary, interest rate cuts are unable to lift spending. Finally, by exploiting the disaggregation of credit card data, we uncover considerable heterogeneity in the effects of monetary policy across spending categories and a stronger impact on higher-income users.

JEL Classification: E21, E52

Keywords: monetary policy

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# Monetary Policy and Credit Card Spending\*

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December 13, 2022

## Abstract

We analyze the impact of monetary policy on consumer spending using credit card data. Because of their high frequency, these data improve identification and allow for a precise characterization of the transmission lags. We find that shocks to short-term interest rates affect spending much more rapidly than shocks to longer-term interest rates. We also detect significant asymmetries. While interest rate rises are contractionary, interest rate cuts are unable to lift spending. Finally, by exploiting the disaggregation of credit card data, we uncover considerable heterogeneity in the effects of monetary policy across spending categories and a stronger impact on higher-income users.

**Keywords:** credit card spending, heterogeneity, monetary policy, transmission

**JEL Codes:** E21, E52

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# 1 Introduction

This paper provides the first assessment of the transmission of monetary policy to consumer spending using confidential credit card data. These data offer two key advantages relative to traditional consumption indicators used in the monetary policy literature. First, credit card data are available at high frequency, providing information on daily transactions. This makes it possible to accurately match the timing of monetary policy shocks around policy announcements with spending data, thus improving the identification of the monetary policy effects. In existing studies, monetary policy shocks have to be aggregated at the lower frequency of traditional consumption data, introducing aggregation bias and reducing the number of usable monetary policy shocks when more announcements occur within the same aggregation period. The daily frequency of credit card data is also helpful to match the timing of other control variables. For example, our econometric framework controls for daily information on COVID-19 cases and the stringency of lockdown measures, without having to aggregate these indicators at lower frequency. Finally, the high frequency of credit card data makes it possible to examine the transmission lags of monetary policy more accurately, revealing new insights about differences in the transmission speed of interest rate shocks at different maturities.

Second, credit card data can be used to test for various forms of potential heterogeneity in the transmission of monetary policy. By providing detailed information on individual transactions, these data can be used to differentiate the impact of monetary policy on spending across different goods and services. Furthermore, credit card companies collect demographic and economic information about the users, making it possible to examine possible heterogeneity in the impact of monetary policy across different segments of the population.

Credit card data may also provide a more precise measurement of consumption. Traditional consumption data constructed by statistical agencies rely heavily on household surveys which are subject to several limitations, such as limited sample size, reporting errors, and time lags between different survey waves. These concerns have become more acute in recent years due to declining response rates in surveys ([Meyer, Mok and Sullivan, 2015](#)). By recording actual expenditures in real-time and for a vast number of users, credit card data may thus overcome these limitations ([Abraham et al., 2022](#)).<sup>1</sup>

Our analysis uses credit card data provided by Fable Data for Germany covering the

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<sup>1</sup>A drawback of credit card data is that they do not cover the full spectrum of consumer purchases, for example big-ticket items like car purchases. Yet credit card data correlate very closely with aggregate consumption data as documented later in the paper.

period 2017–2021.<sup>2</sup> Fable Data collects hundreds of millions of transactions on consumer spending, covering more than 1 million users. To capture monetary policy shocks, we rely on high-frequency movements in financial markets during ECB policy announcements, as compiled by [Altavilla et al. \(2019\)](#). We assess the impact of monetary policy shocks on credit card spending using local projections.

We find that a positive interest rate shock—measured as an increase in the 2-year yield during policy announcements—has a significant negative impact on spending. The effect starts to materialize with a lag of about 6 months and involves a reduction in both the number of credit card transactions and in their average spending amounts. We also document that shocks to short-term interest rates tend to have a much more rapid effect on credit card spending. On the contrary, after controlling for movements in 2-year interest rates, long-term interest rates shocks have no significant effect on spending.

These results complement the literature on the relative effectiveness of conventional versus unconventional monetary policy which has focused so far on the impact on financial markets given the lack of high-frequency macroeconomic data ([Gürkaynak, Sack and Swanson, 2005](#); [Krishnamurthy and Vissing-Jorgensen, 2011](#); [Gilchrist, López-Salido and Zakrajšek, 2015](#); [Gagnon et al., 2011](#); [Swanson, 2021](#)). Our results suggest that conventional policy rate changes have a more rapid and tangible effect on consumption than unconventional tools—such as forward guidance and quantitative easing—that tend to operate on longer term yields. These findings have important policy implications for the ongoing efforts to curb inflation. Given the urgent need to cool down aggregate demand before a possible de-anchoring of inflation expectations, policy rate hikes are preferable to quantitative tightening because they involve shorter transmission lags. Using policy rates to accelerate monetary transmission can also reduce the risk that central banks may end up over-tightening monetary policy before observing the effects on aggregate demand.

We extend the econometric analysis along various dimensions to leverage the identification advantages of credit card data and examine monetary transmission in greater detail. We first show that monetary policy has highly asymmetric effects on spending, depending on the direction of the interest rate movements. While positive interest rate shocks trigger spending contractions, negative interest rate shocks are ineffective in boosting spending. These findings are consistent with recent work based on US data ([Tenreyro and Thwaites, 2016](#); [Angrist, Òscar Jordà and Kuersteiner, 2018](#); [Barnichon and Matthes, 2018](#)) and highlight the need for fiscal policy to support demand during economic downturns.

We then examine how the transmission of interest rate shocks depends on the contem-

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<sup>2</sup>See [www.fabledata.com](http://www.fabledata.com) for more information about Fable Data.

poraneous response of stock prices. As pointed out by [Cieslak and Schrimpf \(2019\)](#) and [Jarociński and Karadi \(2020\)](#), the co-movement between interest rates and stock prices during monetary policy announcements can be used to disentangle exogenous shifts in the monetary stance from information shocks. For example, an exogenous monetary policy tightening should generate an increase in interest rates and decline in equity prices. On the contrary, a monetary policy announcement that provides positive information about the outlook should trigger an increase in both interest rates and equity prices. Consistent with this interpretation of the co-movement between the shocks, we find that positive interest rate shocks coupled with declines in equity prices generate significant spending contractions. Consumer spending tends instead to increase in response to positive interest rate shocks associated with rising equity prices.

Finally, we examine possible heterogeneous effects of monetary policy across spending categories and agents' characteristics. We find that monetary policy impact different economic sectors quite asymmetrically. In particular, while monetary tightening substantially reduces spending on discretionary goods, it boosts spending on consumer staples. This is possibly due to substitution effects. For example, people may respond to a monetary tightening by foregoing spending on restaurant meals while increasing spending on at-home food. We also find evidence that monetary tightening impacts high-income credit card users more strongly, possibly consistent with the theoretical prediction that intertemporal substitution effects are stronger among less financially constrained consumers. Monetary policy does not appear instead to have different effects across gender, age groups, and across on-line versus in-person purchases.

**Related literature.** The paper contributes to a large literature on the effects of monetary policy on household consumption. Early contributions were limited to using macro-level data provided by statistical agencies ([Christiano, Eichenbaum and Evans, 1999](#)). In recent years, the literature has started to provide more granular evidence about the transmission channels of monetary policy using individual level data from household surveys.<sup>3</sup> For example, [Cloyne, Ferreira and Surico \(2020\)](#) find that households with a mortgage respond to monetary policy shocks more strongly than renters and outright homeowners. Household survey data entail, however, significant limitations, namely a low frequency of observation, measurement error in self-reported consumption, and small sample size.

To increase the sample of analysis, new studies have leveraged large administrative data from government registries. Using income and wealth data from tax records in Norway, [Holm, Paul and Tischbirek \(2021\)](#) construct household expenditures at the yearly

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<sup>3</sup>There is also a parallel theoretical literature that examines the heterogeneous effects of monetary policy across households ([Kaplan, Moll and Violante, 2018](#); [Auclert, 2019](#)).

frequency and examine their sensitivity to monetary policy shocks depending on households' liquidity positions.<sup>4</sup> The use of administrative data provides important advantages, such as universal coverage of the population and detailed information about households' balance sheets.<sup>5</sup> However, these types of administrative data are available only at low frequency and do not provide direct information on consumption expenditures which have to be inferred using wealth and income data. Therefore, relative to survey and administrative data, credit card data have the advantage of being available at high frequency and being accurately measured.

To capture monetary policy shocks, the paper draws from the literature on high-frequency identification. This approach uncovers monetary policy surprises by examining movements in financial markets during tight windows surrounding policy announcements. Most studies have focused on the impact of these shocks on financial market variables (Kuttner, 2001; Cochrane and Piazzesi, 2002; Bernanke and Kuttner, 2005; Gürkaynak, Sack and Swanson, 2005; Hanson and Stein, 2015; Gilchrist, López-Salido and Zakrajšek, 2015; Nakamura and Steinsson, 2018). Yet some papers have also used high-frequency identification to study the effects on macroeconomic variables. For example, Gertler and Karadi (2015) aggregate high-frequency monetary shocks at monthly frequency and use them as instrument into a VAR to examine the impact on medium-term credit variables and industrial production.<sup>6</sup> Relative to these papers, our analysis strengthens the identification of the monetary policy transmission by better matching the timing of the monetary policy shocks with daily credit card transactions. This also makes it possible to examine monetary transmission in greater detail, for example looking at differences in the transmission lags associated with different interest rate maturities. Furthermore, we can differentiate the effects of monetary policy across different spending categories and credit card users' characteristics.

The paper is also related to ongoing efforts in the economic profession to harness the transformative potential of Big Data (Einav and Levin, 2014). The vast amount of information collected by private firms and government agencies can greatly facilitate economic monitoring and allow to track the effects of economic shocks and policy actions at the micro level. The COVID-19 pandemic has accelerated work on these issues, with some researchers using credit card data to capture changes in spending patterns in real

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<sup>4</sup>Andersen et al. (2020b) also employ tax data to estimate the impact of monetary policy shocks but focus on the effects on income, wealth, and car purchases.

<sup>5</sup>Administrative data have also been used to examine the consumption response to unemployment and health shocks (Kolsrud et al., 2018; Kolsrud, Landais and Spinnewijn, 2020; Landais and Spinnewijn, 2021).

<sup>6</sup>See also Jarociński and Karadi (2020), Miranda-Agrippino and Ricco (2021) and Andrade and Ferroni (2021).



time and across different goods (Andersen et al., 2020a; Bounie et al., 2020; Chetty et al., 2020; Hacıoğlu-Hoke, Känzig and Surico, 2021). Credit card data have also been used to examine the response of household consumption to unemployment spells (Ganong and Noel, 2019; Andersen et al., 2021) and to document the role of the extensive customer margin in driving retail sales (Einav et al., 2021). In this paper, we showcase their ability to provide novel insights about monetary transmission.

The paper is organized as follows. Section 2 describes the credit card data used in the analysis. Section 3 examines the effects of monetary policy on consumer spending. Section 4 differentiates the effects of monetary policy across spending categories and agents' characteristics. Section 5 concludes.

## 2 Credit card data

The analysis uses confidential credit card data for German households provided by Fable Data. The sample ranges from February 2017 to December 2021. The data reports the spending amounts of individual transactions, including the day of the transaction, the account from which the payment is made, a classification of the merchant category, and whether the transaction took place in person or online. For each credit card account, we observe a few characteristics of the owner, such gender, age group, and an income-level indicator constructed by Fable Data.<sup>7</sup>

Since consumers may open and close credit card accounts, the data is subject to significant consumer growth and churn. To mitigate this aspect, Fable Data uses criteria based on the spending patterns of individual account owners to construct a “core panel” of consumers whose accounts are likely to remain active over time. Fable Data provided us with this core panel consisting of about 160 million transactions across more than 1 million accounts.

Figure 1 illustrates a few key features of the data. Panel 1a shows the spending dynamics over time.<sup>8</sup> Before the pandemic, the yearly growth rate of credit card spending hovered around 10–15 percent, partly reflecting a growing use of credit cards by households. Spending contracted abruptly at the onset of the pandemic in March 2020 and returned to positive growth in the spring of 2021 when health conditions improved and

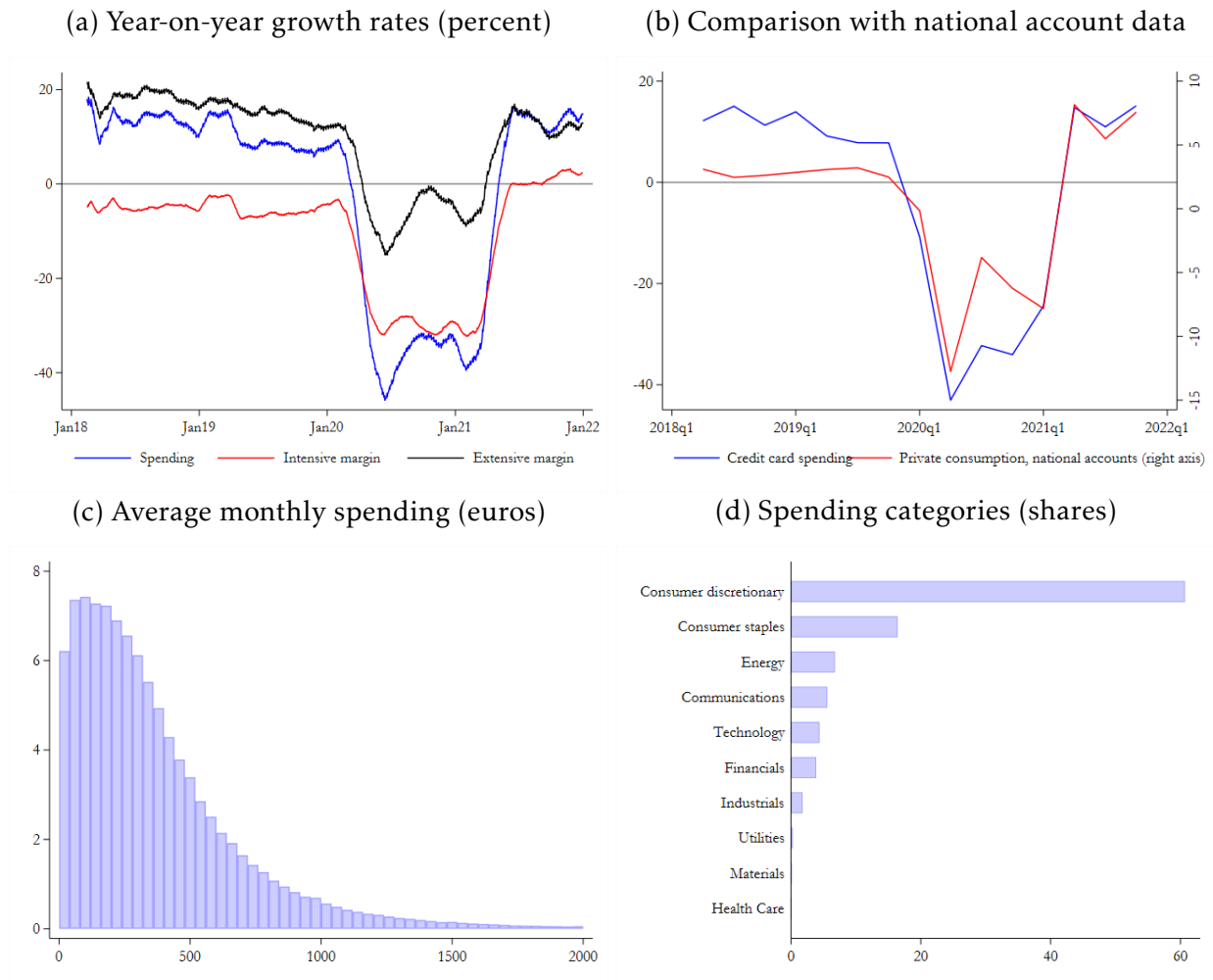
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<sup>7</sup>This income indicator is constructed based on the postcode of where the account is registered. Specifically, each postcode is classified as high (low) income if more than 45 percent of households living there fall into the top (bottom) two quintiles of the national distribution of disposable income.

<sup>8</sup>As pointed out by Chetty et al. (2020) in the case of the US, transaction-level spending data tend to be highly volatile across days of the week, weeks of the month, public holidays, and to some extent due to weather variations. Therefore, we smooth credit card spending using a 90-day moving average and focus on yearly growth rates.

the vaccination campaign began. Panel 1a also illustrates the growth rate in the number of transactions (the extensive margin) and in the average amount of individual transactions (the intensive margin). We see that the number of credit card transactions grew at a rapid pace before the pandemic while the average amount per transactions declined. This reflects the growing penetration of credit card payments which are being used more frequently for smaller purchases. Both the number of transactions and the average spending per transaction declined sharply during the acute phases of the pandemic.

Figure 1: Credit card data, descriptive charts



Notes: Panel 1a shows growth rates at daily frequency. The intensive and extensive margins are computed as spending per transaction and the number of transactions, respectively. All variables are computed as the year-on-year percent change of the 90-day moving average. In panel 1b, credit card data are aggregated at quarterly frequency to be compared with private consumption data from national accounts. Panel 1c shows the distribution of average monthly spending across individual accounts, up to 2000 euros. The spending shares in panel 1d are computed by summing the spending levels for each category across all days and accounts and then dividing them by total spending.

The dynamics of credit card spending are tightly correlated with the those of final private consumption from national account data.<sup>9</sup> This is illustrated in panel 1b where credit card spending is aggregated at the quarterly level to match the frequency of national accounts. This suggests that credit card spending is representative of aggregate spending dynamics. Yet credit card spending misses some important spending categories, notably car purchases and possibly expensive durable goods. The results of the analysis should thus be interpreted as being more indicative of non-durable consumption.<sup>10</sup>

Using the granular information provided by credit card transaction data, panel 1c shows the distribution of average monthly spending in euros across different accounts. The average monthly spending is 357 euros with a standard deviation of 250 euros. The distribution displays most of the density mass below 1,000 euros. However, the right tail is much longer than presented in the chart, with a few accounts exceeding an average spending of 10,000 euros per month.

The data also provide detailed information about spending categories which are constructed by Fable Data based on the type of goods—for example, travel expenses are classified as discretionary spending—and the merchant type—for example, purchases at grocery stores are classified as consumer staples. Figure 1d illustrates the average spending shares. About 60 percent of spending is directed to discretionary consumer products. The second larger spending category includes consumer staples which account for almost 20 percent of total spending.

### 3 The effects of monetary policy on credit card spending

To examine the impact on monetary policy on credit card spending, we use monetary policy shocks identified via high-frequency changes in interest rates around monetary policy announcements. This approach was pioneered by [Kuttner \(2001\)](#) and [Cochrane and Piazzesi \(2002\)](#) and has been used in a large literature referenced in the introduction of the paper. The identification assumption is that interest rate changes in narrow windows around central banks' announcements are driven by unanticipated monetary policy decisions. A caveat to this approach is that interest rate movements associated with monetary policy announcements may also incorporate information effects about the strength of the economic outlook. Later in the analysis, we will show that the results are robust to using more complex econometric specifications that better isolate pure monetary policy

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<sup>9</sup>The correlation coefficient is statistically significant at 90 percent.

<sup>10</sup>Using consumer expenditure data for the US available at monthly frequency, [Miranda-Agrippino and Ricco \(2021\)](#) find that the impact of monetary policy is concentrated on non-durable spending, with no significant effects on durable purchases.

shocks from information effects.

We take data on high-frequency changes in interest rates around ECB monetary announcements from the Euro Area Monetary Policy Event-Study Database (EA-MPD). This dataset is compiled by [Altavilla et al. \(2019\)](#) and provides comprehensive information about movements in interest rates at different maturities.<sup>11</sup> Since during our period of analysis—from 2017 to 2021—the policy rate in the euro area was largely unchanged at -0.4/-0.5 percent, monetary policy largely operated via forward guidance. To account for this aspect, we follow [Hanson and Stein \(2015\)](#) and [Gilchrist, López-Salido and Zakrajšek \(2015\)](#) and use shocks to 2-year yields rather than to very short-term rates in our baseline econometric specifications. Yet by exploiting the high frequency of credit card spending, we will also examine shocks to other interest rate maturities.

To examine the effect of interest rate shocks on credit card spending, we start by estimating the following local projection specification ([Jordà, 2005](#)):

$$\begin{aligned}
 S_{t+h} - S_{t-1} = & \sum_{p=1}^P \beta_p^h I_{t-p} + \sum_{p=1}^P \gamma_p^h \text{cases}_{t-p} + \sum_{p=1}^P \phi_p^h \text{lockdown}_{t-p} + \sum_{p=1}^P \theta_p^h \text{support}_{t-p} \\
 & + \sum_{p=1}^P \rho_p^h S_{t-p} + \alpha^h + \text{dow}^h + \text{doy}^h + \varepsilon_t^h
 \end{aligned} \tag{1}$$

The variable  $S_t$  denotes the log of credit card spending at time  $t$ .<sup>12</sup> The dependent variable is thus the cumulative log difference of credit card spending over the horizon  $h = [0, \dots, 365]$  relative to the value at  $t - 1$ . The main independent variable of interest is the interest rate shock,  $I_{t-p}$ . The regression includes a broad set of control variables. As illustrated in [Figure 1a](#), credit card spending during the sample of analysis was heavily influenced by the COVID-19 pandemic. Therefore, we control for several variables associated with the pandemic, namely the log of the number of COVID-19 infections, *cases*; an index capturing the strictness of lockdown restrictions, *stringency*; and an index summarizing income support and debt relief measures provided during the pandemic,

<sup>11</sup>Data are available at [https://www.ecb.europa.eu/pub/pdf/annex/Dataset\\_EA-MPD.xlsx](https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx). For each ECB policy announcement, the EA-MPD differentiates between market movements surrounding the press release, the subsequent press conference, and over the entire monetary event window—that is from before the press conference to after the press conference. We use market movements over the entire window since household spending should be influenced by monetary policy decisions irrespective of whether they are communicated during the press release or the press conference. We refer the reader to [Appendix A](#) for charts that illustrate the shocks underpinning our analysis. Since the analysis uses credit card data for Germany, we use shocks to German yields although the results are robust to using shocks to the Overnight Index Swap rates.

<sup>12</sup>We use a 90-day moving average for credit card spending to smooth out fluctuations. The results are robust to employing a 30-day or a 7-day moving average.

support.<sup>13</sup>

The regression also controls for lags of the year-on-year log difference of credit card spending,  $s_j = S_j - S_{j-365}$ , to account for the persistence of the dependent variable. We include a week worth of lags (i.e.,  $P = 7$ ). Increasing the number of lags does not materially change the results. Finally, the regression includes day-of-the-week and day-of-the-year fixed effects to control for seasonal patterns during the week and the year. Standard errors are robust to heteroskedasticity and autocorrelation.

The coefficient of interest is  $\beta_p^h$ , which captures the cumulative response of credit card spending to an interest rate shock. Figure 2a shows that an interest rate increase on the 2-year German bond has a statistically significant negative impact on credit card spending which starts to materialize about 6 months after the shock. The effect on spending is economically sizeable, with a one-standard-deviation shock to the 2-year yield reducing credit card spending by up to 1.7 percent. Figure 2b shows that the impact of interest rate shocks on credit card spending operates via both intensive and extensive margins.<sup>14</sup> In other words, a surprise interest rate increase leads to a reduction in the number of transactions as well as in their average amount. The interest rate impact on consumption spending is also robust to deflating nominal spending by CPI inflation, as illustrated in Appendix B.

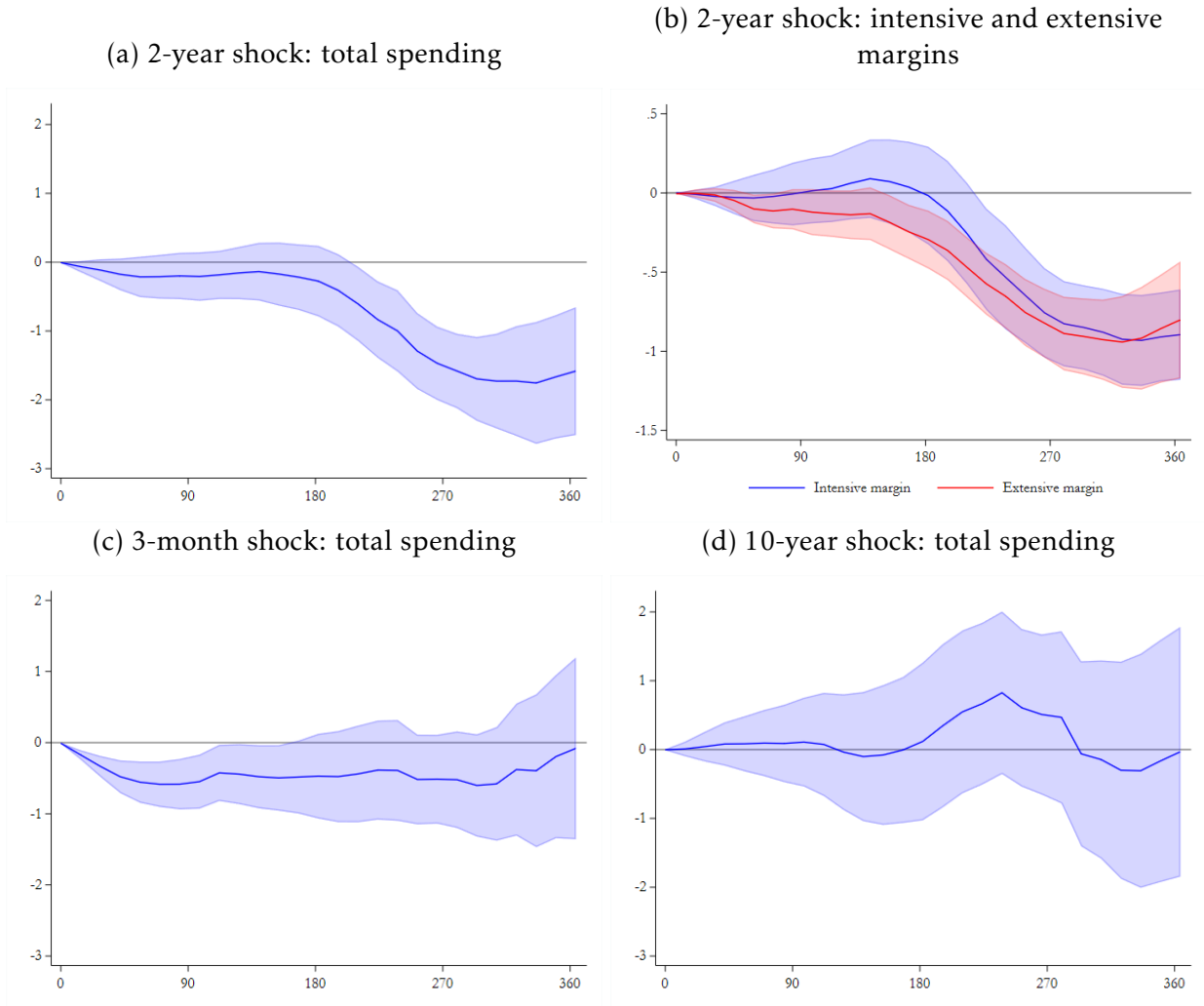
Thanks to the high frequency of credit card data, we can also examine possible differences in the speed of monetary transmission depending on the maturity of the interest rate shock, that is on the specific segment of the yield curve affected by monetary policy. This analysis informs the debate on the relative effectiveness of conventional interest rate policy—affecting short-term rates—versus unconventional tools such as forward guidance and quantitative easing that tend to operate on longer-term interest rates. To compare the effects of interest rate shocks at different maturities, we expand the econometric specification in equation (1) to include interest rate shocks on 3-month and 10-year bond

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<sup>13</sup>The lockdown and economic support indexes are provided by the University of Oxford’s Coronavirus Government Response Tracker. The lockdown index is constructed by averaging nine sub-indicators capturing school closures, workplace closures, cancellations of public events, gatherings restrictions, public transportation closures, stay-at-home requirements, restrictions on internal movement, controls on international traveling, and public information campaigns. The economic support index records if the government is providing direct cash payments to people who lose their jobs or cannot work, and whether the government is freezing financial obligations for households (e.g., stopping loan repayments, banning evictions, among others).

<sup>14</sup>For this exercise, we include in the specification an interaction term between the shock variable and a dummy variable that equals one if the dependent variable is the growth rate of the intensive margin and zero if it is the growth rate of the extensive margin, as well as the dummy variable itself. We then retrieve the impact of monetary policy on the intensive margin by summing the coefficient on the shock variable and the one on the interaction term between the shock and the dummy variable, while the impact on the extensive margin is equal to the coefficient on the shock.

Figure 2: Response of credit card spending to an interest rate shock  
(Percent)



Notes: The figure shows the response of credit card spending to a one-standard deviation interest rate shock. In panel 2a, total spending is computed as the year-on-year percent change of the 90-day moving average of daily credit card spending. In panel 2b, the intensive and extensive margins are computed as the year-on-year percent change of the 90-day moving averages of spending per transaction and the number of transactions, respectively. All regressions include controls for the stage of the pandemic, the stringency of lockdowns, an indicator for income support and debt relief measures, as well as day-of-the-week and day-of-the-year fixed effects. The lines denote the point estimates and the shaded areas correspond to 90 percent confidence intervals.

yields. Figure 2c shows that a one-standard deviation increase in the 3-month yields tends to generate an immediate decline in credit card spending which falls by about 0.8 percent within a month.<sup>15</sup> The negative effect on consumption persists for about 6 months. On the contrary, interest rate shocks to 10-year yields are not associated with statistically significant changes in credit card spending after controlling for 2-year yields, as illustrated in Figure 2d. These results suggest that traditional changes in policy rates are likely to affect household spending quite rapidly via their impact on short-term interest rates. By operating on medium- and long-term rates, forward guidance and quantitative easing appear instead to involve considerably longer transmission lags. In Appendix C we corroborate these results by identifying interest rate shocks due to conventional policy rate changes and unconventional monetary tools using the methodology proposed by Altavilla et al. (2019).

The empirical framework in equation (1) can be flexibly expanded along various dimensions to examine monetary transmission in greater detail. We first examine whether contractionary and expansionary monetary policy shocks have or not symmetric effects on economic activity. This is an enduring question in macroeconomics, dating back to the debate on the effectiveness of monetary policy during the Great Depression. In traditional New Keynesian models with symmetric nominal rigidities, interest rate cuts and hikes have symmetric effects. This is in stark contrast with concerns expressed since the Great Depression whereby monetary stimulus may fail to provide macroeconomic stimulus, being akin to “pushing on a string”. Recent empirical analyses lend support to this latter view, showing that monetary tightening has clear negative effects on activity whereas monetary loosening has weaker effects, often not statistically significant (Tenreyro and Thwaites, 2016; Angrist, Òscar Jordà and Kuersteiner, 2018; Barnichon and Matthes, 2018).

To differentiate between the impact of positive and negative interest rate shocks, we expand equation (1) by interacting the interest rate shocks on 2-year yields with dummy

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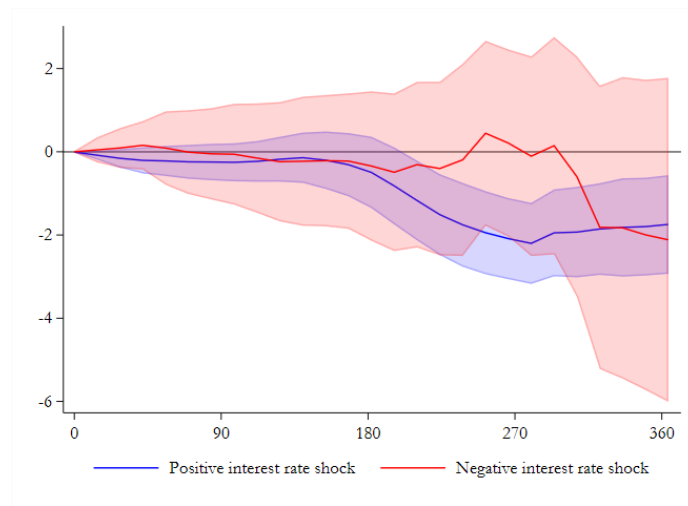
<sup>15</sup>The inclusion of 3-month and 10-year interest rate shocks in equation (1) does not materially change the impact of 2-year shocks. In comparing the quantitative effects of shocks to 2-year and 3-month rates on consumer spending, it is helpful to consider that during the sample of analysis the standard deviation of 2-year shocks is larger than the standard deviation of 3-month shocks, 30 and basis points respectively 21. Thus, an increase in the 3-month yield of a same magnitude to an increase in the 2-year yield would generate a peak contraction in consumer spending by about 1.2 percent.

variables,  $D_{t-p}^+$  and  $D_{t-p}^-$ , denoting whether interest rates increased or declined:

$$\begin{aligned}
 S_{t+h} - S_{t-1} = & \sum_{p=1}^P \left( \bar{\lambda}_p^h + \bar{\beta}_p^h I_{t-p} \right) \times D_{t-p}^+ + \sum_{p=1}^P \left( \underline{\lambda}_p^h + \underline{\beta}_p^h I_{t-p} \right) \times D_{t-p}^- \\
 & + \sum_{p=1}^P \gamma_p^h \text{cases}_{t-p} + \sum_{p=1}^P \phi_p^h \text{stringency}_{t-p} + \sum_{p=1}^P \theta_p^h \text{support}_{t-p} \\
 & + \sum_{p=1}^P \rho_p^h s_{t-p} + \alpha^h + \text{dow}^h + \text{doy}^h + \varepsilon_t^h
 \end{aligned} \tag{2}$$

Figure 3 shows that a positive interest rate shock triggers a significant decline in credit card spending. The impact is more pronounced than illustrated in Figure 2a where the econometric specification did not differentiate between positive and negative interest rate shocks. On the contrary, a negative interest rate shock is unable to stimulate consumption, generating responses that are not statistically significant.

Figure 3: Asymmetric effects of interest rate shocks  
(Percent)



Notes: The figure shows the response of credit card spending to a 2-year interest rate shock, differentiating between positive and negative shocks. Credit card spending is computed as the year-on-year percent change of its 90-day moving average. The regressions include controls for the stage of the pandemic, the stringency of lockdowns, an indicator for income support and debt relief measures, as well as day-of-the-week and day-of-the-year fixed effects. The lines denote the point estimates and the shaded areas correspond to 90 percent confidence intervals.

These results are robust to refining the identification of monetary policy shocks to better account for possible information effects. Sudden increases in interest rates around



monetary policy announcements are generally interpreted as reflecting an exogenous tightening of the monetary stance. The underlying assumption is that private markets and the central bank share the same information set so that any market reaction must reflect shifts in the central bank’s policy stance. However, if the central bank has access to private information or processes public information more efficiently, monetary policy announcements may also reveal information about the economic outlook (Romer and Romer, 2000; Miranda-Agrippino and Ricco, 2021). In this case, a positive interest rate shock could reflect an information shock, whereby markets upgrade their expectations about the outlook and price-in an endogenous monetary policy tightening.

Disentangling these channels is important because a positive interest rate shock driven by an information shock may boost rather than dampen consumer spending. To shed light on this issue, recent work has leveraged the response of stock prices surrounding policy announcements (Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020). A hawkish shift of the monetary policy stance should lead to an interest rate increase coupled with a drop in stock prices. On the contrary, a positive information shock that signals a stronger economic outlook should increase rates as well as boost equity valuations.

To incorporate this identification scheme, we expand the econometric specification in equation (2) and include interaction terms between interest rate movements around policy announcements and contemporaneous stock price responses:

$$\begin{aligned}
S_{t+h} - S_{t-1} = & \sum_{p=1}^P \left( \bar{\lambda}_p^h + \bar{\beta}_p^h I_{t-p} + \bar{\xi}_p^h I_{t-p} \times SP_{t-p} + \bar{\psi}_p^h SP_{t-p} \right) \times D_{t-p}^+ \\
& + \sum_{p=1}^P \left( \underline{\lambda}_p^h + \underline{\beta}_p^h I_{t-p} + \underline{\xi}_p^h I_{t-p} \times SP_{t-p} + \underline{\psi}_p^h SP_{t-p} \right) \times D_{t-p}^- \\
& + \sum_{p=1}^P \eta_p^h SP_{t-p} + \sum_{p=1}^P \gamma_p^h cases_{t-p} + \sum_{p=1}^P \phi_p^h stringency_{t-p} \\
& + \sum_{p=1}^P \theta_p^h support_{t-p} + \sum_{p=1}^P \rho_p^h s_{t-p} + \alpha^h + dow^h + doy^h + \varepsilon_t^h
\end{aligned} \tag{3}$$

The variable  $SP_{t-p}$  captures the change in stock prices—specifically in the Euro STOXX 50 index—surrounding ECB policy announcements. This regression specification can be used to estimate the response of credit card spending to an interest rate shock conditional on the contemporaneous reaction in stock prices.

As illustrated in Appendix A, in most cases interest rate and stock prices moved in

opposite directions during our sample of analysis, denoting a prevalence of monetary policy shocks over information shocks. Yet there are various instances when interest rates and stock prices moved in the same direction, making it possible to differentiate the effects on credit card spending depending on the co-movement between interest rates and stock prices.

Figure 4 illustrates the results. Panel 4a shows that a positive interest rate shock triggers a significant contraction of credit card spending if it is associated with a contemporaneous decline in stock prices, thus capturing a tightening shift in the monetary stance. On the contrary, a positive interest rate shock tends to have expansionary effects on spending when it is coupled with an increase in stock prices, reflecting a positive signaling shock about the strength of the economic outlook.<sup>16</sup> Yet the expansionary effect is shorter lived. This is consistent with the notion that the central bank reacts to positive news about the strength of the economic outlook by endogenously tightening monetary policy to cool down economic activity. Panel 4b considers the effects of a negative interest rate shock. The results corroborate our previous findings. Negative interest rate shocks continue to have no significant effects on credit card spending, irrespective of the reaction in stock prices.<sup>17</sup>

## 4 Heterogeneous effects of monetary policy

Credit card data carry a great potential to shed light on possible heterogeneity in the transmission of monetary policy across spending categories and credit card users. To examine these aspects, we aggregate credit card spending by the group of interest  $i$  (i.e., spending categories, spending types, age groups, and income level) and estimate the fol-

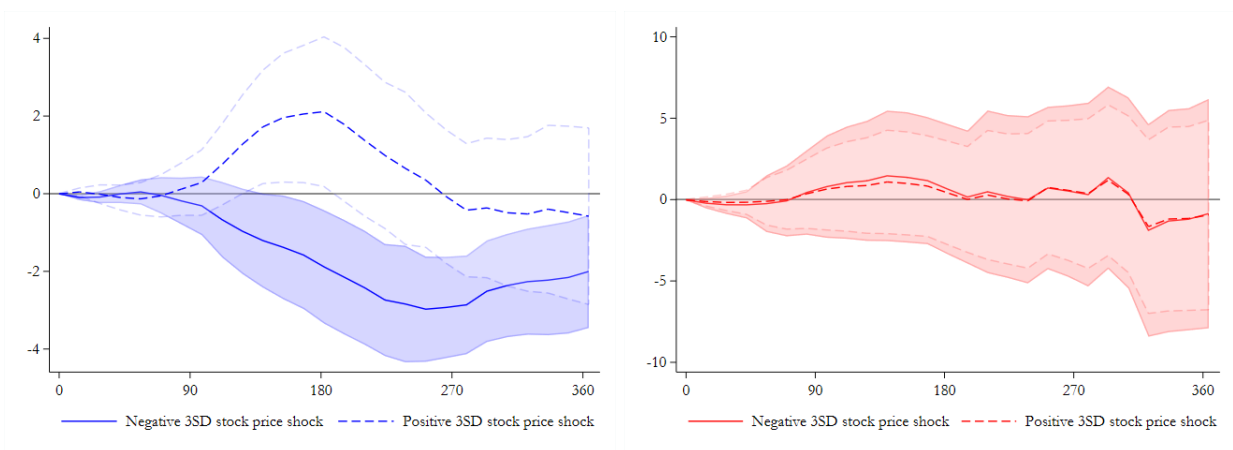
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<sup>16</sup>To confirm that the impulse response functions in panel 4a are statistically different from each other, Appendix D shows that the coefficient  $\bar{\psi}_p^h$  in equation (3) is positive and statistically significant between 4 and 9 months after the shock.

<sup>17</sup>In Appendix D, we also show how positive and negative interest rate shocks affect credit card spending for different values of the stock price response's distribution.

Figure 4: Interest rate shock and stock price response  
(Percent)

(a) Spending reaction to a positive interest rate shock conditional on stock price shock (b) Spending reaction to a negative interest rate shock conditional on stock price shock



Notes: The figure shows the response of credit card spending to an interest rate shock, differentiating between positive and negative shocks and conditional on the stock price response. Credit card spending is computed as the year-on-year percent change of its 90-day moving average. The interest rate shock capture movements of the 2-year German bond during monetary policy announcements. The stock price response capture movements of the Euro STOXX 50 index during monetary policy announcements. All regressions include controls for the stage of the pandemic, the stringency of lockdowns, an indicator for income support and debt relief measures, as well as day-of-the-week and day-of-the-year fixed effects. The lines denote the point estimates and the shaded areas correspond to 90 percent confidence intervals.

lowing panel version of the regression specification in equation (3):

$$\begin{aligned}
S_{i,t+h} - S_{i,t-1} = & \left[ \sum_{p=1}^P \left( \bar{\lambda}_{p,i}^h + \bar{\beta}_{p,i}^h I_{t-p} + \bar{\xi}_{p,i}^h I_{t-p} \times SP_{t-p} + \bar{\psi}_{p,i}^h SP_{t-p} \right) \times D_{t-p}^+ \right. \\
& + \sum_{p=1}^P \left( \underline{\lambda}_{p,i}^h + \underline{\beta}_{p,i}^h I_{t-p} + \underline{\xi}_{p,i}^h I_{t-p} \times SP_{t-p} + \underline{\psi}_{p,i}^h SP_{t-p} \right) \times D_{t-p}^- \\
& + \sum_{p=1}^P \eta_{p,i}^h SP_{t-p} \left. \right] \times G_i + \sum_{p=1}^P \gamma_p^h cases_{t-p} + \sum_{p=1}^P \phi_p^h stringency_{t-p} \\
& + \sum_{p=1}^P \theta_p^h support_{t-p} + \sum_{p=1}^P \rho_p^h s_{t-p} + \alpha_i^h + dow^h + doy^h + \varepsilon_{i,t}^h
\end{aligned} \tag{4}$$

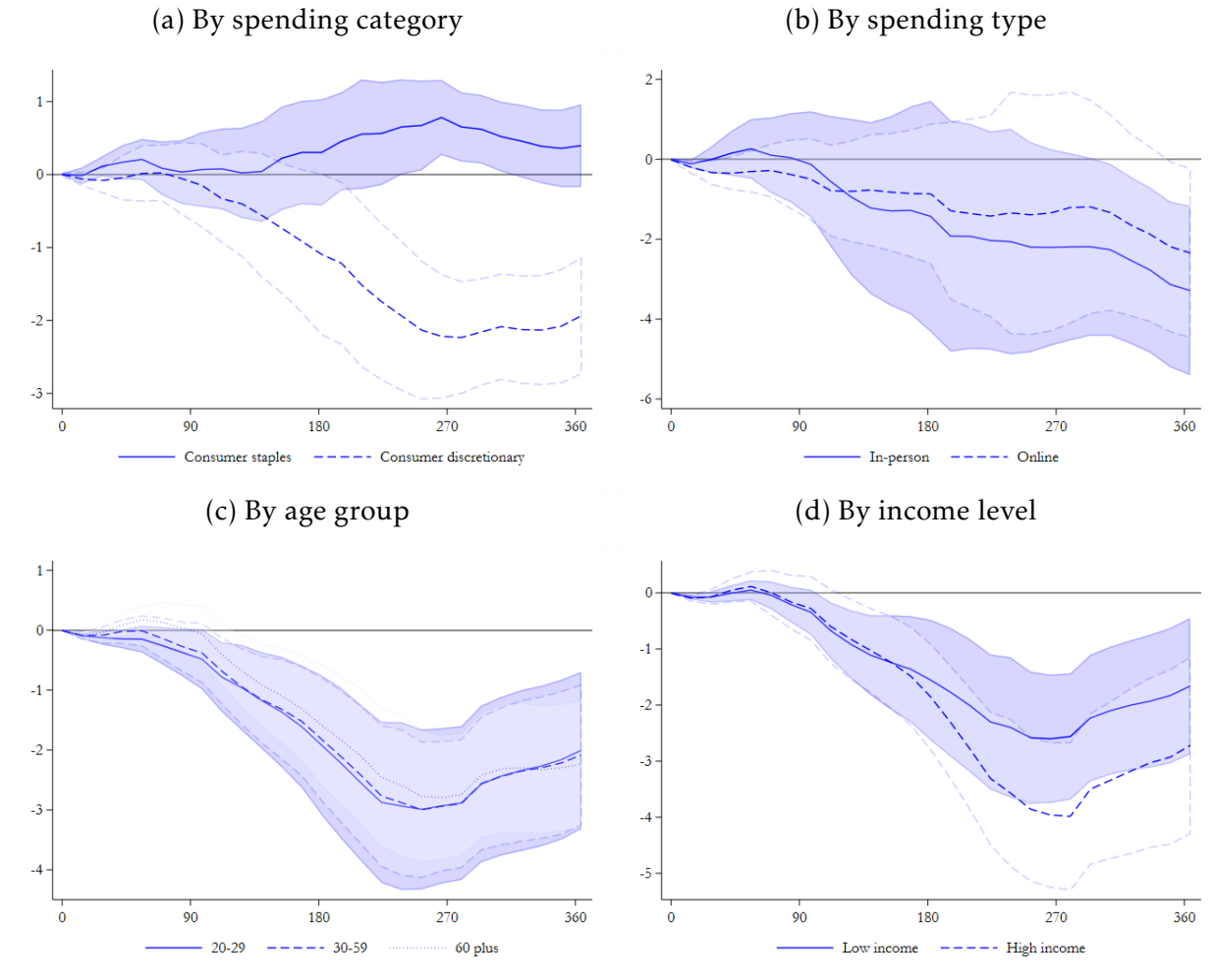
where dummy variable  $G_i$  takes value one when the dependent variable belongs to group  $i$ , and zero otherwise.

Figure 5 illustrate the regression results, focusing on the impact of a positive interest rate shock conditional on a contemporaneous decline in stock prices. Panel 5a shows that monetary tightening has highly heterogeneous effects across spending categories. While consumer discretionary spending contracts strongly, households do not reduce spending on consumer staples. In fact, a monetary tightening appears to modestly increase spending on consumer staples, possibly reflecting substitution effects between discretionary and staple goods. We instead do not find differences in monetary transmission when we differentiate between online and in-person purchases, as shown in panel 5b.<sup>18</sup>

Turning to the characteristics of individual credit card users, we have access to gender and age group information as well to a categorical variable constructed by Fable Data that estimates the income level of the user based on the residential area. Panel 5c shows that monetary transmission does not seem to vary across age groups. We also do not find evidence of differences across gender. Panel 5d suggests instead that monetary tightening has stronger effects on spending by high-income users. This could reflect the fact that high-income consumers are less subject to borrowing constraints and thus react more strongly to intertemporal substitution effects triggered by higher interest rates. In interpreting these results, it is important to consider that income inequality in Germany is less pronounced than in other countries and that credit card users may have a narrower income distribution than the overall population. It will be interesting to revisit this result as better income indicators become available and credit card usage becomes more com-

<sup>18</sup>Note that only about half of the credit card transactions in our sample are differentiated between online and in-person purchases.

Figure 5: Testing for heterogeneous effects of monetary tightening  
(Percent)



Notes: The figure shows the response of credit card spending to a positive interest rate shock, conditional on a negative 3SD stock price response. Credit card spending is computed as the year-on-year percent change of its 90-day moving average. The interest rate shock capture movements of the 2-year German bond during monetary policy announcements. The stock price response capture movements of the Euro STOXX 50 index during monetary policy announcements. All regressions include controls for the stage of the pandemic, the stringency of lockdowns, an indicator for income support and debt relief measures, as well as day-of-the-week and day-of-the-year fixed effects. The lines denote the point estimates and the shaded areas correspond to 90 percent confidence intervals.

mon among the low-income segment of the population. In the future, researches may also gain access to richer information about the characteristics of credit card users once better legal protocols to handle privacy considerations are in place.

## 5 Conclusions

In this paper, we have used novel transaction-level data from more than 1 million credit account accounts in Germany to examine the transmission of monetary policy to household spending. These data provide two key advantages relative to traditional consumption data.

First, they are available at daily frequency. This improves the identification of the monetary policy transmission since spending data can be precisely matched with monetary policy shocks, without the need to aggregate monetary shocks at the lower frequency of conventional consumption data. The analysis finds that increases in 2-year interest rates triggered by monetary policy announcements have a significant negative impact on credit card spending that materializes with a lag of approximately 6 months. Shocks to short-term interest rates involve a much faster transmission to consumer spending while shocks to long-term interest rates have no significant effects after controlling for changes in 2-year rates. These results provide novel evidence about the effects of different monetary policy tools on consumer spending depending on which segment of the yield curve they affect the most.

The analysis also reveals that monetary policy has highly asymmetric effects on household spending. While a monetary tightening generates a pronounced contraction in spending, monetary easing appears ineffective in stimulating consumption. These findings are consistent with recent analyses based on US data and raise profound questions for policymakers on how to best support aggregate demand during downturns. The contractionary effects of interest rate hikes are particularly pronounced if they are coupled with a decline in stock market prices that captures more accurately the effects of an exogenous tightening of the monetary stance. Credit card spending tends instead to increase modestly in response to a positive interest rate shock coupled with a rise in stock prices, reflecting positive information shocks about the economic outlook.

Credit card data offer also a second key advantage relative to traditional consumption data. By collecting information on individual transactions and credit card holders, they can be used to examine monetary transmission at a much more granular level. The paper provides several first insights into this promising area of research. Monetary policy tends to have highly heterogeneous effects across spending categories. For example, a monetary

tightening leads to a strong contraction in discretionary spending but it does not deter spending on staple goods. In fact, spending on staples tends to increase modestly after a monetary tightening possibly because of substitution effects with discretionary goods. We also find evidence that monetary tightening may have stronger effects on higher income households. Monetary policy seems instead to operate similarly on on-line and in-person spending, as well as across gender and age groups.

By demonstrating the potential of credit card data in assessing the impact of monetary policy on consumer spending, the paper opens fruitful avenues for future research. First, ongoing efforts by Fable Data to expand the collection of card transaction data will make it possible to replicate the analysis in other countries, possibly corroborating our findings or revealing important cross-country differences in the transmission of monetary policy. Second, as better protocols to handle privacy concerns are put in place and researchers gain access to more detailed information about credit card users, it will be possible to further investigate how monetary transmission may vary across users' demographic and economic characteristics. Third, the credit card data and empirical approach used in the paper can also be used to examine the effects of other types of shocks, for example those arising from fiscal policy.

## References

- Abraham, Katharine G., Ron S. Jarmin, Brian Moyer, and Matthew D. Shapiro.** 2022. *Big Data for Twenty-First-Century Economic Statistics*. University of Chicago Press.
- Altavilla, Carlo, Luca Brugnolini, Refet S. Gürkaynak, Roberto Motto, and Giuseppe Ragusa.** 2019. “Measuring euro area monetary policy.” *Journal of Monetary Economics*, 108: 162–179.
- Andersen, Asger Lau, Amalie Sofie Jensen, Niels Johannesen, Claus Thustrup Kreiner, Søren Leth-Petersen, and Adam Sheridan.** 2021. “How do households respond to job loss? Lessons from multiple high-frequency data sets.” *CEPR Discussion Paper 16131*.
- Andersen, Asger Lau, Emil Toft Hansen, Niels Johannesen, and Adam Sheridan.** 2020a. “Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data.” *CEPR Discussion Paper 14809*.
- Andersen, Asger Lau, Niels Johannesen, Mia Jørgensen, and José-Luis Peydró.** 2020b. “Monetary policy and inequality.” *CEPR Discussion Paper 15599*.
- Andrade, Philippe, and Filippo Ferroni.** 2021. “Delphic and odyssean monetary policy shocks: Evidence from the euro area.” *Journal of Monetary Economics*, 117: 816–832.
- Angrist, Joshua D., Òscar Jordà, and Guido M. Kuersteiner.** 2018. “Semiparametric estimates of monetary policy effects: String theory revisited.” *Journal of Business & Economic Statistics*, 36(3): 371–387.
- Auclert, Adrien.** 2019. “Monetary policy and the redistribution channel.” *American Economic Review*, 109(6): 2333–67.
- Barnichon, Regis, and Christian Matthes.** 2018. “Functional approximation of impulse responses.” *Journal of Monetary Economics*, 99: 41–55.
- Bernanke, Ben S, and Kenneth N Kuttner.** 2005. “What explains the stock market’s reaction to Federal Reserve policy?” *The Journal of finance*, 60(3): 1221–1257.
- Bounie, David, Youssouf Camara, Étienne Fize, John Galbraith, Camille Landais, Chloé Lavest, Tatiana Pazem, and Baptiste Savatier.** 2020. “Consumption dynamics in the COVID crisis: Real time insights from French transaction & bank data.” *CEPR Discussion Paper 15474*.



- Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, , and the Opportunity Insights Team.** 2020. “The Economic impacts of COVID-19: Evidence from a new public database built using private sector data.” *NBER Working Paper 27431*.
- Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans.** 1999. “Monetary policy shocks: What have we learned and to what end?” *Handbook of macroeconomics*, 1: 65–148.
- Cieslak, Anna, and Andreas Schrimpf.** 2019. “Non-monetary news in central bank communication.” *Journal of International Economics*, 118: 293–315.
- Cloyne, James, Clodomiro Ferreira, and Paolo Surico.** 2020. “Monetary policy when households have debt: New evidence on the transmission mechanism.” *Review of Economic Studies*, 87(1): 102–129.
- Cochrane, John H, and Monika Piazzesi.** 2002. “The Fed and interest rates—a high-frequency identification.” *American Economic Review*, 92(2): 90–95.
- Einav, Liran, and Jonathan Levin.** 2014. “Economics in the age of big data.” *Science*, 346(6210): 1243089.
- Einav, Liran, Peter J Klenow, Jonathan D Levin, and Raviv Murciano-Goroff.** 2021. “Customers and Retail Growth.” *NBER Working Paper 29561*.
- Gagnon, Joseph, Matthew Raskin, Julie Remache, and Brian Sack.** 2011. “The financial market effects of the Federal Reserve’s large-scale asset purchases.” *International Journal of Central Banking*, 7(1): 3–43.
- Ganong, Peter, and Pascal Noel.** 2019. “Consumer spending during unemployment: Positive and normative implications.” *American Economic Review*, 109(7): 2383–2424.
- Gertler, Mark, and Peter Karadi.** 2015. “Monetary policy surprises, credit costs, and economic activity.” *American Economic Journal: Macroeconomics*, 7(1): 44–76.
- Gilchrist, Simon, David López-Salido, and Egon Zakrajšek.** 2015. “Monetary policy and real borrowing costs at the zero lower bound.” *American Economic Journal: Macroeconomics*, 7(1): 77–109.
- Gürkaynak, Refet S, Brian P Sack, and Eric T Swanson.** 2005. “Do actions speak louder than words? The response of asset prices to monetary policy actions and statements.” *International Journal of Central Banking*, 1(1): 55–93.

- Hacıoğlu-Hoke, Sinem, Diego R. Känzig, and Paolo Surico.** 2021. “The distributional impact of the pandemic.” *European Economic Review*, 134: 103680.
- Hanson, Samuel G, and Jeremy C Stein.** 2015. “Monetary policy and long-term real rates.” *Journal of Financial Economics*, 115(3): 429–448.
- Holm, Martin Blomhoff, Pascal Paul, and Andreas Tischbirek.** 2021. “The transmission of monetary policy under the microscope.” *Journal of Political Economy*, 129(10): 2861–2904.
- Jarociński, Marek, and Peter Karadi.** 2020. “Deconstructing monetary policy surprises—the role of information shocks.” *American Economic Journal: Macroeconomics*, 12(2): 1–43.
- Jordà, Òscar.** 2005. “Estimation and inference of impulse responses by local projections.” *American Economic Review*, 95(1): 161–182.
- Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante.** 2018. “Monetary policy according to HANK.” *American Economic Review*, 108(3): 697–743.
- Kolsrud, Jonas, Camille Landais, and Johannes Spinnewijn.** 2020. “The value of registry data for consumption analysis: An application to health shocks.” *Journal of Public Economics*, 189: 104088.
- Kolsrud, Jonas, Camille Landais, Peter Nilsson, and Johannes Spinnewijn.** 2018. “The optimal timing of unemployment benefits: Theory and evidence from Sweden.” *American Economic Review*, 108(4-5): 985–1033.
- Krishnamurthy, Arvind, and Annette Vissing-Jorgensen.** 2011. “The effects of quantitative easing on interest rates: Channels and implications for policy.” *Brookings Papers on Economic Activity*, 215–265.
- Kuttner, Kenneth N.** 2001. “Monetary policy surprises and interest rates: Evidence from the Fed funds futures market.” *Journal of Monetary Economics*, 47(3): 523–544.
- Landais, Camille, and Johannes Spinnewijn.** 2021. “The value of unemployment insurance.” *Review of Economic Studies*, 88(6): 3041–3085.
- Meyer, Bruce D., Wallace K. C. Mok, and James X. Sullivan.** 2015. “Household Surveys in Crisis.” *Journal of Economic Perspectives*, 29(4): 199–226.

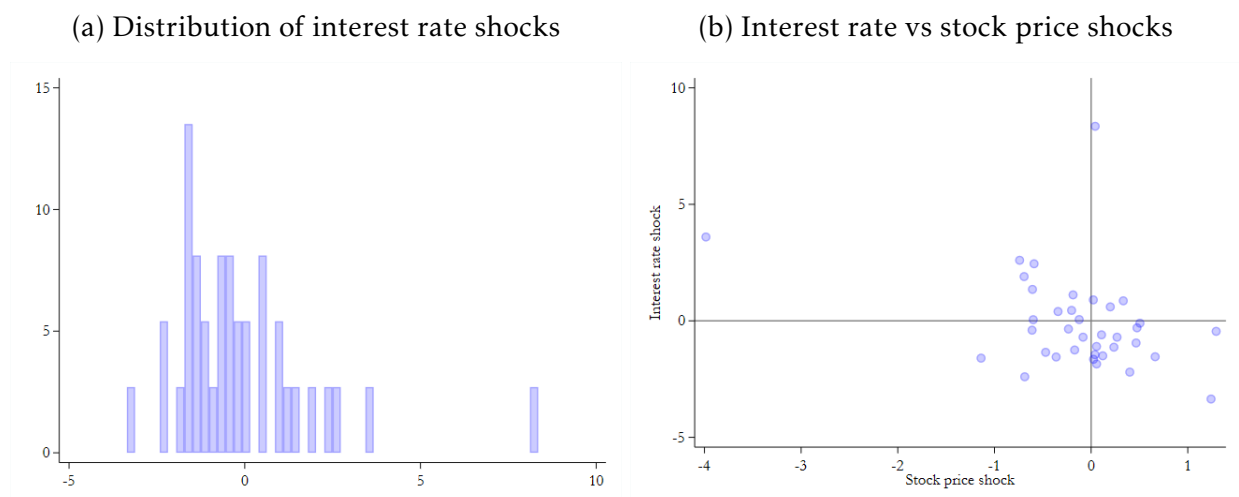
- Miranda-Agrippino, Silvia, and Giovanni Ricco.** 2021. “The transmission of monetary policy shocks.” *American Economic Journal: Macroeconomics*, 13(3): 74–107.
- Nakamura, Emi, and Jón Steinsson.** 2018. “High-frequency identification of monetary non-neutrality: The information effect.” *Quarterly Journal of Economics*, 133(3): 1283–1330.
- Romer, Christina D., and David H. Romer.** 2000. “Federal Reserve information and the behavior of interest rates.” *American Economic Review*, 90(3): 429–457.
- Swanson, Eric T.** 2021. “Measuring the effects of federal reserve forward guidance and asset purchases on financial markets.” *Journal of Monetary Economics*, 118: 32–53.
- Tenreiro, Silvana, and Gregory Thwaites.** 2016. “Pushing on a string: US monetary policy is less powerful in recessions.” *American Economic Journal: Macroeconomics*, 8(4): 43–74.

# Appendix

## A Interest rate shocks

Figure A.1a shows the distribution of shocks to 2-year German bond yields during our period of analysis. Data are retrieved from the Euro Area Monetary Policy Event-Study Database, compiled by [Altavilla et al. \(2019\)](#). The figure shows that the shocks are fairly symmetrically distributed around zero. Figure A.1b presents a scatter plot between the interest rate shocks and stock market shocks. In almost 60 percent of the cases, interest rates and stock prices moved in opposite directions, consistent with the effects of exogenous changes in the stance of monetary policy.

Figure A.1: Interest rate and stock price shocks around ECB announcements  
(basis points)

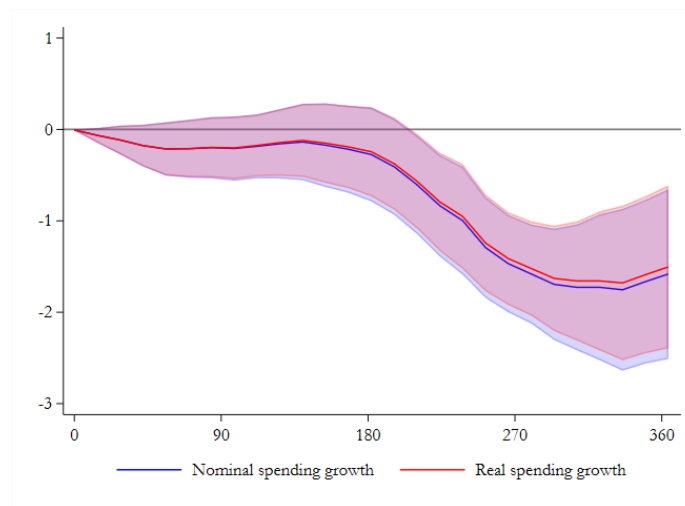


Notes: Panel A.1a reports the distribution of interest rate shocks defined as changes in the the 2-year yield on German bond around monetary policy announcements between 2017 and 2021. Panel A.1b presents a scatter plot of changes in the 2-year yield against concomitant changes in the Euro STOXX 50.

## B Real vs nominal spending

Figure B.1 shows the response of credit card spending to a 2-year interest rate shock, differentiating between nominal and real spending. Real spending is computed by deflating the nominal amount by monthly CPI. The figure shows that the impact of monetary policy on credit card spending is largely unchanged no matter whether spending is deflated by CPI or not.

Figure B.1: Response of nominal vs real credit card spending to an interest rate shock (Percent)



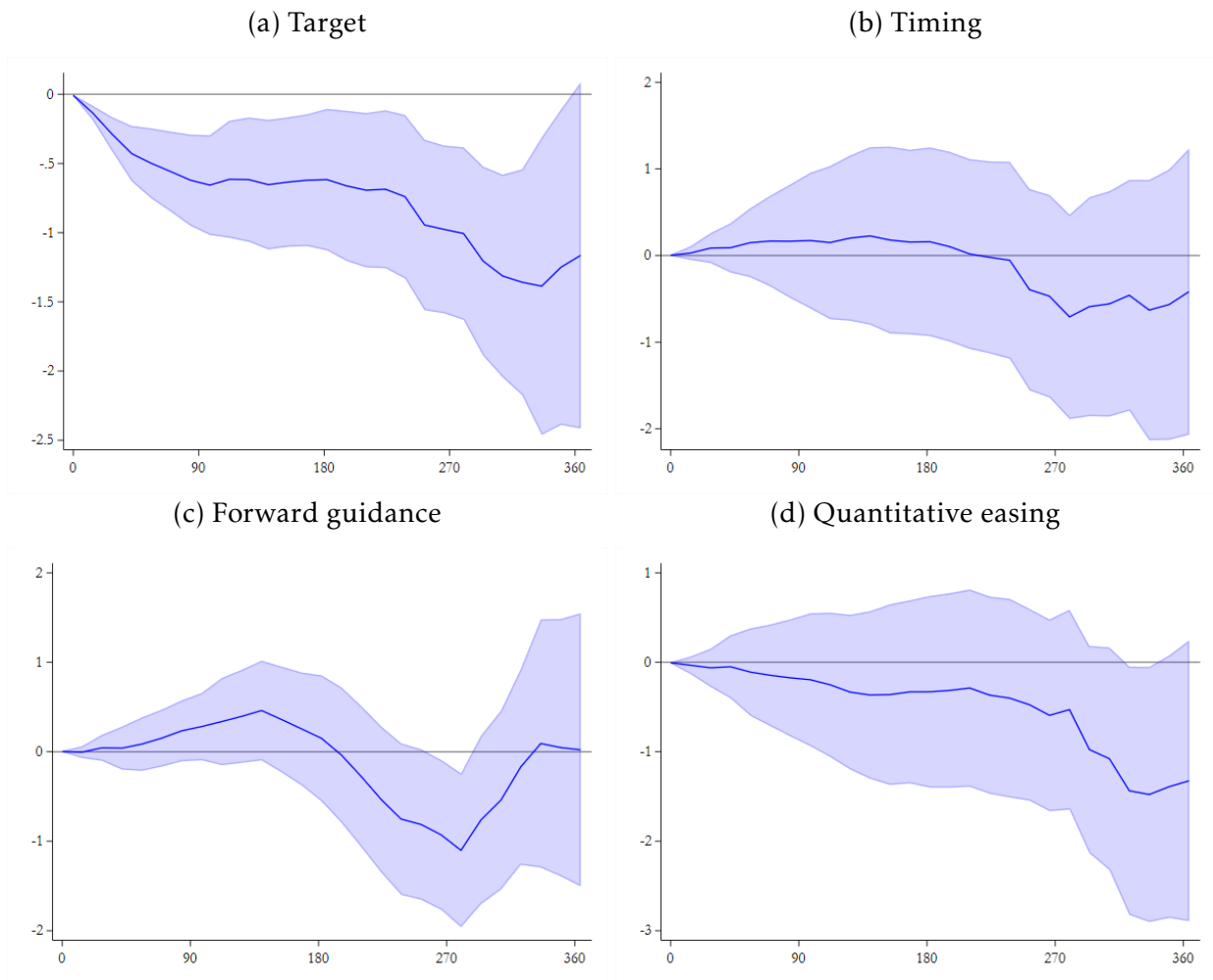
Notes: Credit card spending is computed as the year-on-year percent change of its 90-day moving average. The interest rate shock capture movements of the 2-year German bond during monetary policy announcements. The stock price response capture movements of the Euro STOXX 50 index during monetary policy announcements. All regressions include controls for the stage of the pandemic, the stringency of lockdowns, an indicator for income support and debt relief measures, as well as day-of-the-week and day-of-the-year fixed effects. The lines denote the point estimates and the shaded areas correspond to 90 percent confidence intervals.

## C Monetary policy shock types and credit card spending

[Altavilla et al. \(2019\)](#) estimate latent factors using yield changes at different maturities during the ECB’s monetary policy announcements. By rotating these factors with suitable restrictions, they extract shocks that can be matched to specific monetary policy tools. [Altavilla et al. \(2019\)](#) find one statistically significant factor during the ECB’s press release window and 3 factors during the subsequent press conference window. The factor during the press release window loads on short-term rates and is thus interpreted as a shock to the “target” policy rate. The three factors during the press release window are instead interpreted as a “timing” shock—capturing market expectations about interest rate changes over the next few meetings—a “forward guidance” shock, and “quantitative easing” shocks.

Figure [C.1a](#) shows that “target” shocks tend to have an immediate impact on credit card spending, consistent with the results presented in Figure [2c](#) about the fast transmission of short-term interest rates. The other shocks, especially those associated with forward guidance and quantitative easing, involve considerably longer transmission lags with peak effects on consumption materializing between 9 and 11 months after the shock.

Figure C.1: Response of credit card spending to different monetary policy shocks (Percent)

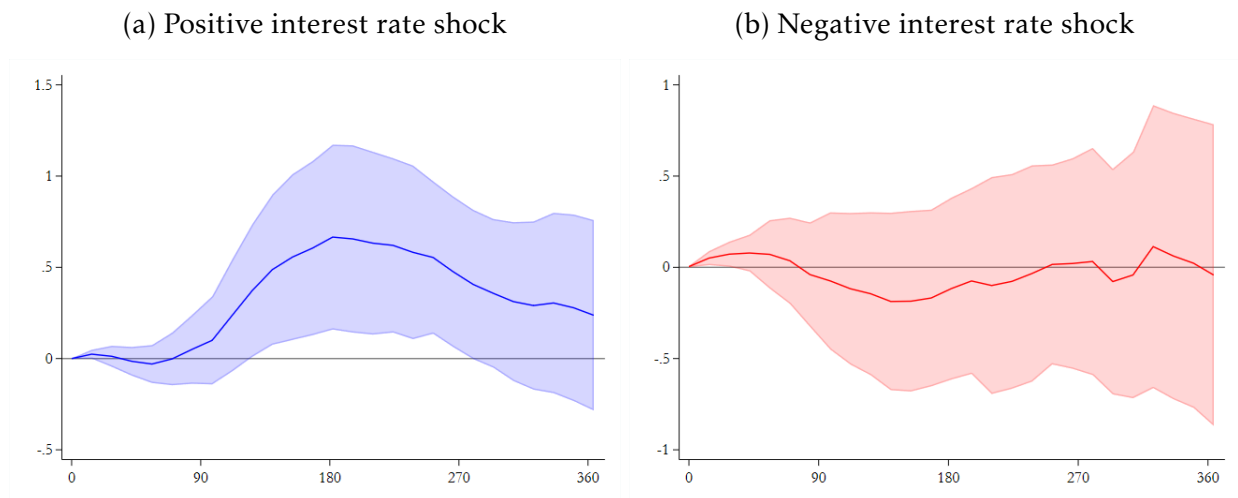


Notes: Panels (a) to (d) are derived from a specification that includes all factors.

## D Interactions between interest rate and stock price shocks

Figure D.1 illustrates the regression coefficients on the interaction terms between the interest rate shocks and stock price shocks in equation (3). Panel D.1a shows the coefficient  $\overline{\psi}_p^h$  on the interaction term when the interest rate shock is positive. This coefficient is positive and statistically significant between 4 and 9 months after the shock, implying that positive interest rate shocks have less contractionary effects on spending—in fact, potentially expansionary effects—if stock prices increase. Panel D.1b shows instead that the coefficient  $\underline{\psi}_p^h$  is not statistically different from zero. This implies that movements in stock prices do not affect the transmission (or lack thereof) of negative interest rates to household spending.

Figure D.1: Interaction between interest rate and stock price shocks  
(Percent)



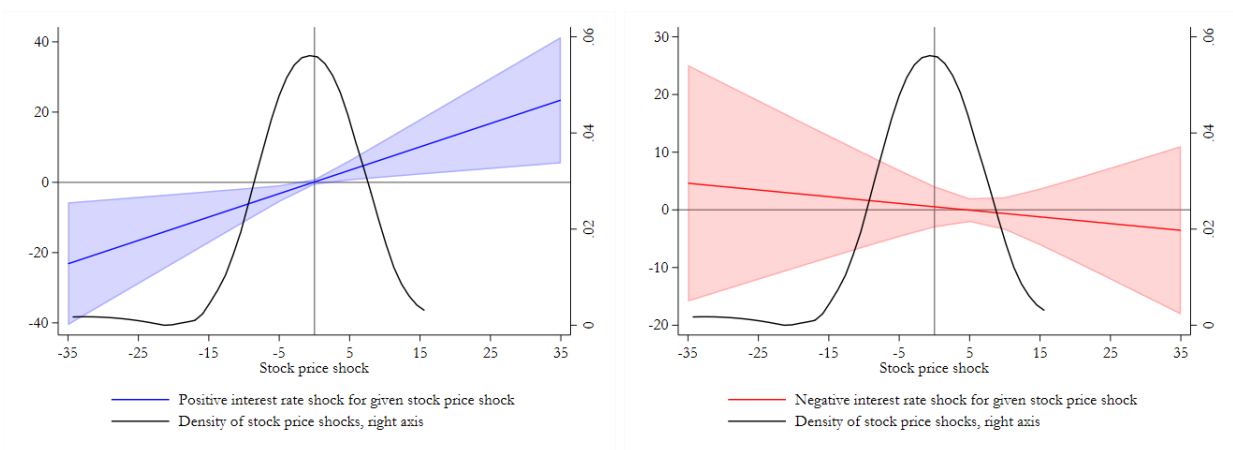
Notes: The lines denote the point estimates of the interaction coefficients between interest rate and stock price shocks in equation (3). The shaded areas correspond to 90 percent confidence intervals.

Figure D.2 plots the estimated impact of credit card spending to an interest rate shock over the entire distribution of the stock price response. Panel D.2a and D.2b display the response to a positive and a negative interest rate shock 6 months after the monetary policy event, respectively. Most of the density of stock price changes lies between -15 and 15 standard deviations. Over this range of values, the estimated impact of an interest rate increase on credit card spending goes from -9.8 to 10.1 percent and it is statistically significant. A decline in interest rates, on the other hand, does not produce any significant change in spending regardless of the size of the stock price response.



Figure D.2: Response of credit card spending to an interest rate shock after 6 months  
(Percent)

(a) Spending reaction to a positive interest rate shock conditional on stock price shock (b) Spending reaction to a negative interest rate shock conditional on stock price shock



Notes: The figure shows the response of credit card spending to an interest rate shock, differentiating between positive and negative shocks and conditional on the stock price response. Credit card spending is computed as the year-on-year percent change of its 90-day moving average. The interest rate shock capture movements of the 2-year German bond during monetary policy announcements. The stock price response capture movements of the Euro STOXX 50 index during monetary policy announcements. All regressions include controls for the stage of the pandemic, the stringency of lockdowns, an indicator for income support and debt relief measures, as well as day-of-the-week and day-of-the-year fixed effects. The lines denote the point estimates and the shaded areas correspond to 90 percent confidence intervals.