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The Bank Lending Channel
A Time-Varying Approach

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Abstract

Using a cross-country panel of 925 banks from 19 advanced economies, for the period 1981-2016, I examine how the bank lending channel of monetary policy has evolved over time. I find that the sensitivity of lending to bank balance sheet liquidity declines over time, with nearly all the reduction occurring between the early 1990s and the early 2000s. Contrary to normal times, during recessions, more liquid banks reinforce the impact of monetary policy shocks on lending relative to their less liquid counterparts. The sensitivity of non-interest income to lending increases sharply from the late 1990s till the global financial crisis of 2008, and declines in the post-crisis period, indicating pro-cyclicality. Moreover, the relative ability of banks with higher non-interest income to mitigate monetary policy shocks increases sharply towards the end of the sample period, capturing the impact of the prolonged low interest rate environment on transmission process. These findings suggest that the structural changes in the banking industry and the state of the economy have a significant impact on the strength of the bank lending channel.

Keywords: bank lending channel, monetary policy, financial regulation.

JEL codes: E51, E52, E44.

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1 Introduction

During the two decades prior to the global financial crisis, there were significant shifts in the banking industry. While this transformation began as early as in the 1970s in the United States, it gathered pace through 1990s and 2000s throughout the developed world. Traditional deposit-taking institutions, across many advanced economies, ventured beyond merely managing deposits and making loans to add investment banking, market making, venture capital, and proprietary trading to their activities.[1] In addition to this shift in focus towards non-core banking activities, business models too experienced a transformation during this period as banks began to replace traditional originate-to-hold model of lending with the originate-to-distribute (OTD) model. Therefore, it is conceivable that the bank lending channel — the impact of bank-specific characteristics on banks' credit supply and the concomitant differentiated lending responses to monetary policy shocks — has evolved over time.

Yet, the empirical literature on the topic assumes a time invariant coefficient to examine this component of the monetary transmission mechanism. Such an approach restricts our ability to discern how the strength of the bank lending channel vary. Consequently, little is known about how the bank lending channel of the monetary

[1]For example, the FT article, "How Deutsche Bank's high-stakes gamble went wrong" (November 9, 2017) provides a detailed non-technical narrative on the transformation of the bank from a domestically focussed traditional deposit-taking institution to a global bank with a substantial focus on non-core activities.

policy has evolved over a long period of time. Understanding the scale and direction of the changes can inform monetary policy, financial regulation, and coordination of both. In this paper I address this gap in the literature.

To explore whether the bank lending channel of monetary policy varies over time, I make use of bank balance sheet data from Worldscope. My sample consists of 925 banks in 19 advanced economies during the period between 1981 and 2016. The cross-country data allows me to focus on within-bank and within-country-year variations mitigating key endogeneity concerns in the literature.[2]

Using standard dynamic panel data estimation techniques, I estimate the sensitivity of lending to liquidity in banks balance sheet, and find a positive and statistically significant correlation between them. Furthermore, I examine if monetary policy affects this relationship, and find that monetary policy tightenings increase banks' lending sensitivity to liquidity. In other words, the more liquidity a bank has the more it lends, and is better able to mitigate monetary policy shocks. These results provide evidence for the existence of a bank lending channel. While there is no clear consensus in the literature on the strength of the bank lending channel, these findings are broadly in line with what is documented in a large number of papers starting with the seminal contribution of Kashyap and Stein (2000). Introducing additional

[2]The use of both bank-level and country-year-level fixed effects in my specification allows me to control for i.) effects of any country-level macroeconomic variable on lending; and ii.) reverse causality from lending to monetary policy shocks. Please see the methodology section for a detailed discussion.

bank-level controls — namely, measures capturing size, leverage, and non-interest income — both individually and interacted with monetary policy do not affect the results discussed above. Notably, I find a positive and statistically significant correlation between lending and the share of non-interest income in total revenue, a bank balance sheet component that has received much attention in the post-crisis academic and policy discussions.

Next, I allow all the above estimated coefficients to vary over time, by estimating rolling regressions. This exercise, the key novelty of the paper, provides us an overall picture of how the bank lending channel has evolved over time. While I find that the sensitivity of lending to liquidity remains statistically significant throughout the period under consideration, its magnitude declines over time. Nearly all of this reduction occurs between the early 1990s and the early 2000s. The coefficient on the interaction term between liquidity and monetary policy suggests that during recessions more liquid banks reinforce the impact of monetary policy shocks on lending relative to their less liquid counterparts. It underscores the importance of balance sheet liquidity measures in mitigating disruption of credit supply to the real sector during recessions.

I find non-interest income to be an increasingly important determinant of bank lending. The sensitivity increases sharply and becomes statistically significant from the late 1990s onwards till the global financial crisis of 2008. While it continues to be statistically significant, it declines in magnitude in the post-crisis period, indicating the highly pro-cyclical nature of non-interest income in determining lending. Moreover, the relative ability of banks with higher non-interest income to mitigate monetary policy shocks increases sharply towards the end of the sample period. This sharp increase is indicative of the growing relative importance of non-interest income during a prolonged low interest rate environment. These results are unaffected by the length of the window for rolling regressions. It holds for 3, 4, 5, 6, 7, and 8 year window estimations.

The findings of the paper are in line with the stylised understanding of the changes in banking industry and associated lending behaviour exhibited by banks. It makes two contributions to the literature on the bank lending channel. First, it documents the evolution of the bank the lending channel over a period of thirty years in a group of advanced economies, something that has not been done in the literature before. Second, it suggests that the bank lending channel could be a time-varying phenomenon reflecting structural changes in the industry and state of the economy, offering an explanation for the lack of conclusive evidence on the magnitude of the bank lending channel in the existing empirical literature.

The findings of the paper have policy relevance. First, the results reiterate the need for larger bank balance sheet liquidity buffers. This would not only reduce liquidity risks but also mitigate the disruption of the bank lending channel of monetary policy transmission during recessions. Second, the growing importance of non-interest income underscores the need to intensify the monitoring and supervision of non-core activities of banks. For instance, regulators could consider requiring stricter disclosure of the composition of banks' non-interest income. Finally, the findings of the paper are also an important reminder about the time-varying nature of some of the key relationships we rely on in our policy analysis, and urges us to explore time dimension further.

The rest of this paper is organized as follows. Section 2 provides a brief review of empirical literature on the bank lending channel. Section 3 discusses the methodological approach adopted in this paper. Section 4 presents a brief summary of the data and descriptive statistics. Section 5 documents the evolution of the bank lending channel over time. Section 6 offers concluding remarks with some caveats.

2 Literature review

The bank lending channel of monetary policy has been the subject of a large body of literature starting with the seminal contributions of Bernanke and Blinder (1988, 1992) and Bernanke and Gertler (1995). Bernanke and Blinder (1992) in their empirical analysis show that aggregate bank lending shrinks in response to monetary policy tightening. However, such a decline could reflect a reduction in overall credit demanded as the economy slows down in response to tighter monetary policy, rather than a contraction of loans supplied by banks.[3]

Using bank balance sheet data, Kashyap and Stein (1995, 2000) propose a solution to disentangle credit supply from credit demand. Specifically, the authors argue that the relative ease, or lack thereof, with which a bank can raise uninsured deposits after a monetary policy tightening will determine its lending outcomes. Relying on heterogeneity in bank-specific characteristics, they identify the differential impact of the monetary policy shock on banks. They argue that bank-specific features only influence loan supply and not loan demand. They propose size and liquidity to be relevant bank-specific characteristics for such an identification strategy. In other words, they demonstrate larger and more liquid banks to be able to better mitigate the impact of monetary policy shocks on lending relative to their small and less liquid peers.

With the introduction of this methodology by Kashyap and Stein (2000), there has been an explosion in empirical literature that estimates the response of bank lending to bank-specific features and how these features influence changes to lending in response to monetary policy shocks.

The studies that followed utilize balance sheet data and bank heterogeneity in

[3]A related strand of literature identifies borrower rather than bank characteristics, primarily size, to be an important driver of differentiated lending responses. It notes that bank credit to smaller firms contracts more relative to larger firms in response to a negative monetary policy shock. See Gertler and Gilchrist (1994, 1993) and Gilchrist *et al.* (1995). This line of research could be potentially revisited in the context of deleveraging and derisking that occurred in advanced economies, especially in Europe, in the aftermath of the crisis.

similar frameworks to explore the issue, broadly, on two fronts. First, to discuss in detail which specific bank characteristic form the ideal proxy for a bank's ability to raise uninsured deposits, which ultimately drives lending responses to changes in monetary policy. Second, to seek evidence for the bank lending channel in different countries and understand the drivers of cross-country heterogeneity (Peek and Rosengren, 1995; Cecchetti, 1999; Kishan and Opiela, 2000; Altunbaş *et al.*, 2002; Kakes and Sturm, 2002; Angeloni *et al.*, 2003; Gambacorta, 2005).[4] However, the literature does not find a conclusive evidence, in terms of quantity and quality, for the bank lending channel of the monetary policy.

This methodological approach discussed above is not without drawbacks. First, as indicated by Kashyap and Stein (2000) themselves and highlighted by Ciccarelli *et al.* (2015), the use of micro data and bank heterogeneity for identifying the bank lending channel does not capture the full extent of drop in lending from monetary policy tightening. It only captures the contraction in lending owing to liquidity constraints (or any other bank-specific characteristic used to proxy banks' ability to raise uninsured deposits). To overcome this issue, Ciccarelli *et al.* (2015) propose a macro identification that relies on survey data. Second, implicitly, Kashyap and Stein (2000) assume that all banks, including banks with different liquidity levels, face similar changes in

[4]Broadly, the literature suggests size, liquidity, and capital as the three important bank-specific characteristics for accounting for the differentiated responses, while competition, sector health, relationship lending, and networks are pointed out as the relevant financial market characteristics. This is well documented in Dwarkasing *et al.* (2016), an excellent survey of the empirical literature on the bank lending channel of monetary policy.

loan demand in response to a monetary policy shock, which may not be the case. With credit registry data that provide the loan application information as opposed to just realized lending captured in balance sheets, this assumption can be relaxed and provide a cleaner identification, overcoming this drawback as demonstrated by Jiménez *et al.* (2012), Jiménez *et al.* (2014) and Ioannidou *et al.* (2014). Even this approach does not alleviate the concerns indicated in Ciccarelli *et al.* (2015). Moreover, the accessibility of credit registry data remains difficult, and largely restricted to central bank staff.

With the global financial crisis highlighting the importance of financial intermediaries, and banks specifically, in the provision of credit, there has been attempts to revisit this strand of literature. Researchers have attempted to understand how the bank lending channel behaved during the crisis and whether it responded to the unconventional monetary policies introduced in the aftermath of the crisis. Gambacorta and Marques-Ibanez (2011) augments the empirical specification introduced in Kashyap and Stein (2000), and further developed by Ehrmann *et al.* (2003) and Ashcraft (2006), by introducing a crisis dummy to document the developments during the financial crisis. They find that banks with weaker core capital positions, greater dependence on market funding and on non-interest sources of income restricted the loan supply more strongly during the crisis period. They also discuss how as a result of financial innovation and changes to business models, the standard bank-specific indicators used in the literature for finding the pure supply side responses of bank lending to changes in monetary policy might not capture the full impact.

In a similar framework, Borio and Gambacorta (2017) uses a low interest rate environment dummy to examine the effectiveness of monetary policy in stimulating a low interest rate environment. They find that reductions in short-term interest rates are less effective in stimulating bank lending growth when rates reach a very low level and further argue that the impact of low rates on the profitability of banks' traditional intermediation activity explain this observation. Valencia (2017) shows that banks can exhibit self-insurance with loan supply contracting when uncertainty increases. Salachas *et al.* (2017) and Heryán and Tzeremes (2016) focus on sub-samples to examine the difference between pre-crisis and post-crisis years.

3 Methodology

In this context, I attempt to understand how the bank lending channel has evolved over time. The idea is similar to Blanchard *et al.* (2015) who estimate time-varying Phillips Curves to examine how the effect of the unemployment gap on inflation vary over time. They show that: (i) since the mid-1970s, short-run inflation expectations have become more stable; and (ii) the slope of the Phillips curve has flattened over time, with nearly all of the decline taking place from the mid-1970s to the early 1990s, and the coefficient remaining roughly constant since then. They provide a neat set of empirical findings that offers useful insights for current policy deliberations including the ongoing discussion on "the mystery of missing inflation."[5]

Specifically, I ask the following two questions: i) Have there been changes over time in how bank lending responds to different bank-specific characteristics? ii) Has the influence of bank-specific characteristics on how banks' lending responds monetary policy changed over time? On the one hand, it is possible that, over time, due to structural changes in the banking industry (for example, the advent of originate-to-distribute (OTD) model), or financial sector more generally (for example, the increasing prominence of institutional investors or shadow banking in financial intermediation), balance sheet variables traditionally identified to be an important driver of bank lending might have reduced in significance. Concurrently, other balance sheet variables might have also increased in their importance as a determinant of bank lending. Gambacorta and Marques-Ibanez (2011) provide a detailed discussion on the impact of structural changes in the banking industry on the bank lending channel of the monetary policy. On the other hand, these relationships might vary with business cycle fluctuations. During crises, banks might exhibit strategic behaviour. Acharya *et al.* (2010) present a model of banks' choice of ex ante liquidity that is driven by strategic considerations of acquiring assets at fire-sale prices. Moreover,

[5]The phrase is to characterise the economic environment that has existed since mid-2016 where a period of moderate economic expansion has not led to a concomitant increases in inflation in many advanced economies. See BIS Quarterly Review, September 2017, for a detailed discussion.

such changes could also have an impact on to what extent monetary policy changes can elicit differential responses from banks based on balance sheet characteristics.

To this end, I estimate the following baseline specification adapted from the framework initially proposed by Kashyap and Stein (2000) and further developed by Ehrmann *et al.* (2003):

$$l_{b,c,t} = \beta l_{b,c,t-1} + \delta' X_{b,c,t-1} + \gamma_x(\Delta i_{c,t} \times x_{b,c,t-1}) + \alpha_b + \theta_{c,t} + \epsilon_{b,c,t} \tag{1}$$

where l is the growth rate in nominal bank lending (defined as the change in log of total nominal loans) of bank b in country c at time t.

X is a vector of bank level variables capturing bank-specific characteristics. It includes *size* (the log of total assets), *liq* (cash and securities over total assets in percentage), *lev* (a measure to control for leverage defined as common equity as a percentage of total deposits), and *nii* (non-interest income over total revenues in percentage, a control for activities other than core deposit taking and lending, such as investment banking and trading). All bank level variables are lagged by a year to mitigate any potential endogeneity concerns.

$\Delta i_{c,t}$ is the change in three month interbank rate, an interest rate measure that captures the policy rate as well as the marginal cost of short-term funding for banks.

$\Delta i_{c,t}$ is included in the specification as an interaction term with x, individual components of X. Consider liq for example. The coefficient on the interaction term captures the impact of monetary policy on banks' lending behaviour differentiated by the degree of liquidity in their balance sheets. This strategy, as discussed earlier, helps identify pure supply side effects. Liquidity, however, is just one among many bank-specific characteristics that could cause a differentiated response in the provision of credit in response to policy shocks. Therefore, it is important to consider the role of other pertinent bank-specific characteristics in banks' response to policy shocks. I address this concern by adapting equation 1 to include other bank-specific characteristics interacted with $\Delta i_{c,t}$.

α_b and $\theta_{c,t}$ are bank and country-year fixed effects respectively. Exploiting the cross-country variation in data, I choose the specific combination of fixed effects to mitigate two key endogeneity concerns in the literature. First, it is possible that there could be macroeconomic shocks that directly affect lending or jointly affect the state of the banking sector and monetary policy decisions. The use of country-year fixed effects allows me to control for any domestic macro shocks that affect lending or jointly affect both lending and monetary policy. Such a strategy avoids the need for macro controls and renders a simple specification. Second, it is possible that the state of the banking sector itself could affect monetary policy decisions. This is a lesser concern while relying on bank level data as the likelihood of developments specific to a single bank affecting the course of monetary policy is low. Nevertheless, if the bank under stress is systemically important or is a large lender in a small country with a highly concentrated banking industry this might be a serious concern. By including country-time fixed effects, I am able to focus on the within bank variation of the loan growth and the within country-year variation of changes in monetary policy. This mitigates any obvious reverse causality concern that the banking sector situation itself could influence monetary policy. Bank fixed effects and country-year fixed effects, along with lagged bank level variables, allay endogeneity concerns. The use of country-year fixed effects, however, is not without trade-offs. It results in the exclusion of interest rates on its own in equation 1. Since the overall negative relationship between interest rates and bank credit outcomes is well documented, I prefer to include country-year fixed effects for a cleaner identification.

I estimate the specification using Blundell–Bond system generalized method of moments (GMM) estimator. GMM methodology has become a standard empirical approach in the literature, as the fixed effects estimation results in biased estimators as outlined by Nickell (1981) given the dynamic setting. Since I undertake the asymptotically more efficient two-step estimation, I report robust standard errors following Windmeijer (2005) that provide finite-sample correction for the downward bias in standard errors. I also report p-values for Arellano-Bond test for no autocorrelation (second order) in the error term.

As a first step, I run the above specification for the whole sample for all available years. Results from this exercise provide a check on standard results in the literature. However, this approach still does not provide us any answers on the evolution of parameters over time. To understand the evolution of the coefficients, the key focus of this paper, I perform rolling window estimation of the benchmark regression, an approach similar to the one adopted in Jasova *et al.* (2016) to analyse the evolution of exchange rate pass through over time. I report the results for 5-year windows. However, also undertake robustness check for 3, 4, 6, 7, and 8 year windows.

Using the rolling estimates based on equation 1, I can answer the two questions posed earlier. The vector δ provides insights into the first question that asks to what extent the bank-specific characteristics influence lending growth and how has that influence evolved over time. A positive and significant δ_{liq} would indicate that the larger the amount of liquidity a bank has, the more it lends, for example. The coefficient γ_{liq} on the other hand would answer to what extent liquidity helps a bank amplify or mitigate the influence of a monetary policy shock on bank lending outcomes. A positive and statistically significant γ_{liq} would imply that less liquid banks curtail their lending more than their counterparts with more liquid balance sheets. In other words, a relatively more liquid bank mitigates the impact of monetary policy on bank lending. Conversely, a negative and statistically significant γ_{liq} would indicate that a more liquid bank reinforces the impact of monetary policy on bank lending relative to less liquid counterparts.

4 Data

All bank level variables, described in the earlier section, are taken from Worldscope accessed through Datastream. The sample consists of an unbalanced annual panel of 925 banks from 19 advanced economies for the period 1981-2016. Table 1 summarizes the distribution of banks across countries based on the dependent variable, lending growth. The sample, however, is dominated by US banks, an issue I will discuss in robustness checks. A small proportion of banks exit and reenter the panel. This is unlikely to cause any systematic bias given exit and reentry is driven by data reporting issues and is independent of any variables considered in my analysis. I winsorize all bank level variables at both tails using 1% cutoff values. While the number of banks and time period covered in the panel varies marginally across control variables considered, it does not affect the sample meaningfully.

Interest rate data are taken from the OECD, except for Japan and Singapore. Short term rates provided by the OECD are usually either the three month interbank offer rate attaching to loans given and taken amongst banks for any excess or shortage of liquidity over several months or the rate associated with Treasury bills, Certificates of Deposit or comparable instruments, each of three month maturity. For Euro Area countries the 3-month "European Interbank Offered Rate" is used from the date the country joined the euro. I take Japanese rates from Datastream. For Singapore, I use data provided by Monetary Authority of Singapore until 1994, and thereafter the series provided by Datastream. Finally, I provide list of all variables and their definitions in Table 2, and report the descriptive statistics in Table 3.

5 Results

5.1 Baseline specification

I start by estimating equation 1 for the whole sample to assess the bank-specific determinants of the lending outcomes and their influence over the response of bank lending to changes in the monetary policy stance.

Column 1 in Table 4 shows the estimates for the baseline regression 1 for all banks in my sample. δ_{liq} is positive and statistically significant. This result implies that more liquid banks lend more. The point estimate indicates that a one standard deviation increase in liquidity (30.2% in the sample considered) is associated with 11.2 percentage points increase in banks' lending growth.

γ_{liq} too is positive and statistically significant. This result shows that if interest rate increases lending sensitivity to liquidity increases. It suggests that more liquid banks are better able to buffer their lending decisions from monetary policy shocks. In terms of a monetary policy tightening shock, this would imply that more liquid banks contract lending by a smaller amount than its less liquid peers. The point estimate indicates that a one standard deviation increase in $\Delta i_{c,t}$ (1.46 percentage points) is associated with a 5.1 percent increase in the elasticity of lending to liquidity. The lending elasticity to liquidity increases from 0.357 in country-years with a 0.99 decrease in interest rates (corresponding to the 25th percentile in my sample) to 0.376 for country-years with 0.39 increase in interest rates (corresponding to the 75th percentile in my sample), a 5.3 percent increase.

While the baseline results from column 1 provide evidence for the existence of the bank lending channel, it is possible that these results could be driven by omitted variables. Specifically, there could be other bank-specific characteristics that affect banks ability to raise uninsured deposits in the aftermath of a monetary policy shock. To alleviate any such concerns, I introduce additional bank-specific controls into the baseline specification. The results are reported in in Table 5. Columns 2-5 include measures for bank size, leverage ratio and the share of non-interest income individually (columns 2-4) and jointly (column 5).

At the outset, I note that the inclusion of bank level controls does not affect my main finding that more liquid banks lend more and an increase in interest rate increases the sensitivity of banks' lending to liquidity. Both the coefficients (δ_{liq} and γ_{liq}) are positive and statistically significant, and effectively unchanged in magnitude compared to column 1.

δ_{size} is negative and statistically significant when included both individually and jointly. Again, a result in line with the literature suggesting that as banks grow large its ability to grow further declines. δ_{lev} too is positive and statistically significant. However, it reduces in its significance in column 5 when we include all bank specific characteristics.

When *nii* is included both individually and jointly, δ_{nii} is positive and statistically significant as well as of comparable magnitudes, a noteworthy result. The result is in line with the expected sign put forward in the literature. It indicates that banks with more *nii* lend more. The point estimate in column 5 indicates that a one standard deviation increase in *nii* (11.8% in the sample considered) is associated with 5.7 percentage points increase in banks' lending growth. The variable is of interest due to the volatile nature of the non-interest income component of banks' income and associated cyclical variation expected in its influence on lending decisions.[6]

5.2 Additional interactions

Like *liq*, other bank-specific characteristics could also cause a significant differentiated response in the provision of credit by banks in response to monetary policy shocks. I consider this possibility in the set of regressions summarized in Table 5. I augment the specification further by introducing *size*, *lev*, and *nii* interacted with

[6]For instance, Brunnermeier *et al.* documents that banks with higher non-interest income have a higher contribution to systemic risk than traditional banking.

$\Delta i_{c,t}$ individually (columns 1-3) and jointly (column 4).

None of the results from Table 5 are affected by the inclusion of additional interaction terms. The three key findings holds. δ_{liq}, γ_{liq} and δ_{nii} are positive and statistically significant as well as of broadly same magnitude in all the estimations reported in Table 4. I note that γ_{liq} is only significant at 90% confidence interval in column 5 of Table 4. As before, δ_{size} and δ_{lev} too are statistically significant.

γ_{size} is positive and statistically significant at 90% confidence interval, both individually and jointly. That is, a larger bank is better able to mitigate monetary policy shocks. The coefficients on interaction terms for lev and nii, γ_{lev} and γ_{nii}, however, do not have a statistically significant.

Finally, in column 5, as a robustness check and for the purpose of comparison, I report the results of a regression that replaces country-year fixed effects with country and year fixed effects. This allows me to include Δi on its own. The results show that my main findings are robust to the use of alternate specification and as expected the coefficient on Δi is negative and statistically significant. Going forward, I use the specification reported in column 4 with country-year fixed effects for reasons discussed in the methodology section.

5.3 Evolution of the parameters

In this section, I present a series of graphs plotting the value of the key coefficients over time obtained from 5-year rolling regressions. These graphs are based on the specification reported in column 4 of Table 5 that includes all bank level controls, their interactions with the Δi, and bank and country-year fixed effects.

Figure 1 plots the evolution of δ_{liq} for over three decades, covering the period between 1981 and 2016. The labels on the x-axis corresponds to the end period of the rolling regression window (i.e. for example, the y-axis value corresponding to year 1986 in the graph represents the coefficient for liq from the regression covering the period 1981-1986, and so on). The grey shaded area indicates 95% confidence interval band and the pink shaded areas indicate US recessions according to NBER's recession dates. The evolution of δ_{liq} indicates that the influence of liquidity over banks' lending decisions has remained statistically significant through time. Its magnitude, however, has declined gradually over time. Almost all of this decline takes place from the early 1990s to the early 2000s. From its peak of 0.69 in 1994, δ_{liq} declines to 0.26 in 2002, corresponding to a drop of over 60%. The gradual nature of the decline could be a by product of the structural changes in the banking industry including changes to the business models such as the advent of OTD model, potentially requiring them to hold lower amounts of liquid assets in turn affecting lending sensitivity to liquidity.

Figure 2 depicts the evolution of γ_{liq}. A key observation stands out. During the recessions captured in the sample, γ_{liq} dips into negative territory. This implies that during recessions more liquid banks reinforce monetary policy shocks. In other words, a monetary policy loosening shock would cause more liquid banks to expand lending by a larger amount than its less liquid peers.[7] It underscores the importance of balance sheet liquidity measures in mitigating disruption of credit supply to the real sector and aiding policy in that process. However, in recent years γ_{liq} has become positive again, and increased steeply. The sign switching noted here raises an important question: does monetary policy elicit asymmetric responses?

Next, I turn to the behaviour of δ_{nii} and γ_{nii} as summarised in Figures 3 and 4. There is a sharp increase in δ_{nii} in the run up to the global financial crisis from 0.03 in 1999 to 0.59 in 2008. During this period, unlike previously, δ_{nii} also becomes statistically significant, providing further evidence for the increasing influence of non-interest income on lending outcomes. While the coefficient has continued to remain statistically significant in the post-crisis period, it declines in magnitude. The result indicates the highly pro-cyclical nature of the nii in determining banks' lending behaviour. These results could also reflect the changes that occurred in global banking during great moderation such as the shift away from traditional banking activities

[7]Traditionally, the literature has interpreted coefficients using a monetary policy tightening shock, which could be a counter-intuitive means to think about policy response and transmission mechanism during crises.

exhibited by global banks.[8]

γ_{nii} hovers around zero for most part of the sample. Nevertheless, it exhibits a steep increase towards the end of the sample. The result indicates that increasingly banks with higher *nii* are better able to mitigate monetary policy shocks compared to banks with lower *nii*. A period of prolonged low, and in some jurisdictions negative, interest rate regime could offer the explanation for this observation. In addition, the transition from an accommodative monetary policy stance to gradual tightening, provides a macro environment where banks with higher shares *nii* buffer the impact of monetary policy shocks on lending.

I provide further details on the results from 5-year rolling regressions in the Appendix: Additional Tables and Figures. Table 6 provides the descriptive statistics for all the coefficients from 5-year rolling regressions. Figures 5, 6, 7, and 8 visualise δ_{size}, γ_{size}, δ_{lev}, and γ_{lev} respectively.

Finally, the results from 5-year rolling regressions reported in this section are unaffected by changing the length of rolling window. The patterns described for individual coefficients here are robust to the use three, four, six, seven, and eight year windows for rolling regressions estimates.

[8] Activities ranging from investment banking, market making, venture capital, and proprietary trading can be included in this category.

6 Conclusion

This paper studies how the bank lending channel of the monetary policy has evolved over time. I find that the sensitivity of lending to liquidity has declined over time with nearly all the decline occurring between the early 1990s and the early 2000s. The coefficient remains more or less constant since. During US recessions, unlike in normal times, more liquid banks reinforce the impact of monetary policy shocks on lending relative to their less liquid counterparts. I also find that the sensitivity of lending to non-interest income increases sharply from the late 1990s till the global financial crisis of 2008. Moreover, in recent years, banks with a higher share of non-interest income are better able to mitigate monetary policy shocks. These patterns do not depend on the choice of rolling window for estimation: 3, 4, 5, 6 and 8-year rolling windows all show the same pattern.

However, there are two caveats to be borne in mind when reading these results. First, the results, apply only for the group of countries, and not for individual economies, an important caveat. Second, since the capital ratio variable is only available for a substantially smaller time frame and a lower number of banks, it is excluded as a bank-specific variable in the rolling regressions.

The results have significant relevance for policy, particularly in improving our understanding of the transmission of monetary policy changes to credit supply through the bank lending channel. Such cross-country narratives might inform how structural transformations affect the transmission process. In addition, a nuanced understanding of how the influence of bank specific characteristics might vary cyclically provide insights into how to think about monetary policy responses during recessions. The growing, yet highly pro-cyclical, influence of non-core components of banks' income also offers insights towards preventing amplification of credit cycles, and their spillovers into economic growth outcomes. Thus, it is highly relevant for to the discussions on macroprudential regulation, and coordination between monetary and regulatory policies. Finally, the results are an important reminder about the time-varying nature of some of the key relationships we rely on in our policy analysis.

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7 Tables

Table 1: Number of banks by country and growth rate of total loans

Country	Banks	Observation	Start Year	Final Year
Australia	8	202	1981	2016
Austria	6	144	1990	2016
Belgium	3	81	1981	2016
Canada	10	274	1981	2016
Denmark	22	384	1987	2016
France	19	398	1981	2016
Germany	7	135	1981	2016
Greece	6	123	1995	2016
Ireland	3	70	1984	2016
Italy	18	365	1981	2016
Japan	91	1981	1987	2016
Netherlands	3	25	2000	2016
Norway	24	256	1989	2016
Portugal	4	91	1986	2016
Singapore	3	79	1987	2016
Spain	6	92	1988	2016
Switzerland	26	580	1985	2016
United Kingdom	17	232	1981	2016
United States	649	9941	1981	2016

Table 2: Variable Description

All variables are divided by total assets unless specified otherwise.

Variable	Description	Source
l	Change in log of total nominal loans (%)	Worldscope
$size$	Log of total assets	Worldscope
liq	Cash & securities as a share of total deposits (%)	Worldscope
lev	Common equity as a share of total deposits (%)	Worldscope
nii	Non-interest income as a share of total deposits (%)	Worldscope
i	Three month interbank interest rate (%)	OECD & Datastream

Table 3: Descriptive Statistics

This table shows descriptive statistics for the sample reported in Table 1.

	Mean	**Median**	**Std. Dev.**	**Min**	**Max**	**P25**	**P75**	**N**
Bank-level Variables								
l	8.70	7.19	15.40	-25.30	69.29	-0.08	15.19	15453
$size$	15.01	14.65	2.26	11.24	21.07	13.19	16.66	15453
liq	41.49	35.25	30.15	9.42	232.32	25.58	47.49	15453
nii	18.25	15.65	11.76	1.10	60.88	9.72	24.43	15453
lev	12.55	10.99	8.53	2.32	59.86	7.97	14.20	15453
Country-level Variables								
i	4.91	4.02	4.37	-0.78	19.91	1.34	7.12	596
di	-0.36	-0.23	1.46	-5.20	5.25	-0.99	0.39	588

Table 4: System GMM Estimations: Whole Sample

This table reports the results of a set of (Blundell and Bond, 1998) regressions where the dependent variable is the bank lending growth (l_t) and the explanatory variables are lags of lending growth (l_{t-1}), size ($size_{t-1}$), liquidity (liq_{t-1}), leverage (lev_{t-1}), non-interest income (nii_{t-1}), and the interaction between liq_{t-1} and the change in three month interbank rate (Δi_t). Arellano-Bond test for no autocorrelation (first and second order) in the error term is reported in the tables. The regression covers 19 countries for the time period 1981-2016. For the difference equation, the instruments include all available available lags of the endogenous variable and the lag of the first difference of all other regressors. For the level equation, the the endogenous variable is instrumented with its own the lagged first difference.

	(1)	(2)	(3)	(4)	(5)
l_{t-1}	0.007	-0.009	-0.004	-0.004	-0.026*
	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)
liq_{t-1}	0.370***	0.390***	0.316***	0.355***	0.354***
	(0.033)	(0.041)	(0.035)	(0.032)	(0.039)
$liq_{t-1} \times \Delta i_t$	0.014***	0.014***	0.015***	0.012**	0.012***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$size_{t-1}$		-17.480***			-17.482***
		(1.380)			(1.487)
lev_{t-1}			0.570***		0.201*
			(0.098)		(0.113)
nii_{t-1}				0.419***	0.482***
				(0.064)	(0.075)
Observations	14,435	14,435	14,435	14,435	14,435
Number of b	915	915	915	915	915
p-value AR(2)	0.426	0.381	0.307	0.310	0.254
Bank FE	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES

Windmeijer-corrected robust standard errors reported in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Table 5: System GMM Estimations: Additional Interactions

This table reports the results of a set of (Blundell and Bond, 1998) regressions where the dependent variable is the bank lending growth (l_t) and the explanatory variables are lags of lending growth (l_{t-1}), size ($size_t$), liquidity (liq_{t-1}), leverage (lev_{t-1}), non-interest income (liq_{t-1}), and all their interactions with the change in three month interbank rate (Δi_t). The regression covers 19 countries for the time period 1981-2016. Arellano-Bond test for no autocorrelation (first and second order) in the error term is reported in the tables. The regression covers 19 countries for the time period 1981-2016. For the difference equation, the instruments include all available available lags of the endogenous variable and the lag of the first difference of all other regressors. For the level equation, the the endogenous variable is instrumented with its own the lagged first difference.

	(1)	(2)	(3)	(4)	(5)
l_{t-1}	-0.026*	-0.026*	-0.026*	-0.026*	0.590***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.033)
liq_{t-1}	0.354***	0.354***	0.354***	0.353***	0.093***
	(0.039)	(0.039)	(0.038)	(0.040)	(0.010)
$liq_{t-1} \times \Delta i_t$	0.011**	0.012***	0.012**	0.010*	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$size_{t-1}$	-17.446***	-17.498***	-17.485***	-17.446***	-1.414***
	(1.467)	(1.440)	(1.503)	(1.484)	(0.121)
lev_{t-1}	0.200*	0.204*	0.202*	0.203*	0.010
	(0.112)	(0.110)	(0.114)	(0.108)	(0.028)
nii_{t-1}	0.476***	0.477***	0.483***	0.477***	0.099***
	(0.069)	(0.065)	(0.073)	(0.068)	(0.018)
$size_{t-1} \times \Delta i_t$	0.143*			0.157*	0.307***
	(0.084)			(0.082)	(0.067)
$lev_{t-1} \times \Delta i_t$		0.002		0.011	-0.034*
		(0.019)		(0.019)	(0.017)
$nii_{t-1} \times \Delta i_t$			0.010	-0.001	-0.047***
			(0.015)	(0.016)	(0.016)
Δi_t					-2.710***
					(0.977)
Observations	14,435	14,435	14,435	14,435	14,435
Number of b	915	915	915	915	915
p-value AR(2)	0.231	0.258	0.248	0.231	0.000
Bank FE	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	NO
Country FE	NO	NO	NO	NO	YES
Year FE	NO	NO	NO	NO	YES

Windmeijer-corrected robust standard errors reported in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

8 Figures

Figure 1: 5-Year Rolling Regressions: The coefficient on liq (δ_{liq})

This figure plots δ_{liq} over time from 5-year rolling regressions based on column 5 in Table 5. The labels on the x-axis corresponds to the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.

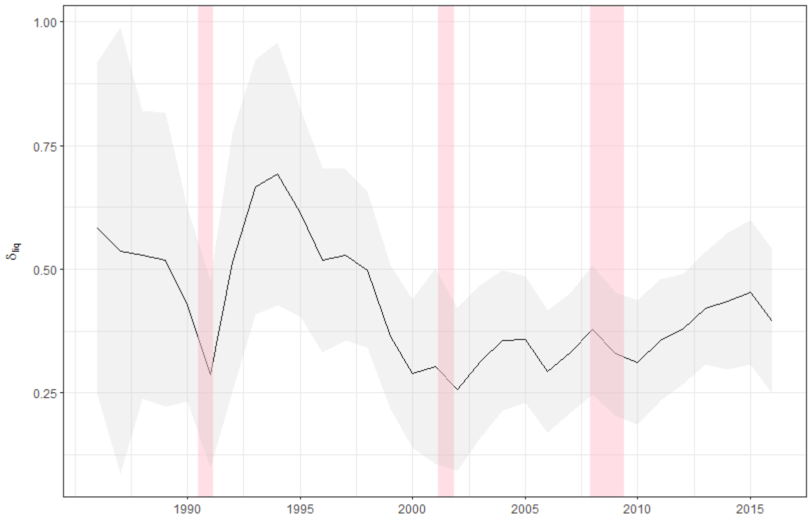


Figure 2: 5-Year Rolling Regressions: The coefficient on $liq_{t-1} \times \Delta i_t$ (γ_{liq})

This figure plots γ_{liq} over time from 5-year rolling regressions based on column 5 in Table 5. The labels on the x-axis corresponds to the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.

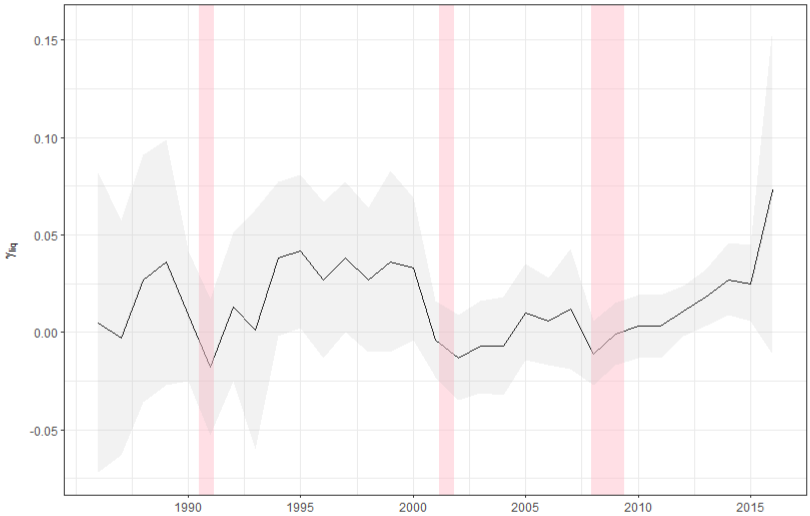


Figure 3: 5-Year Rolling Regressions: The coefficient on nii (δ_{nii})

This figure plots δ_{nii} over time from 5-year rolling regressions based on column 5 in Table 5. The labels on the x-axis corresponds to the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.

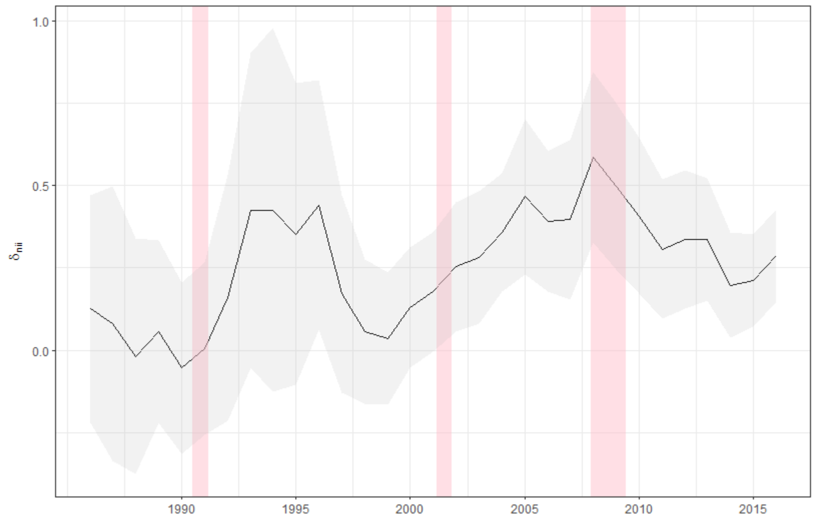
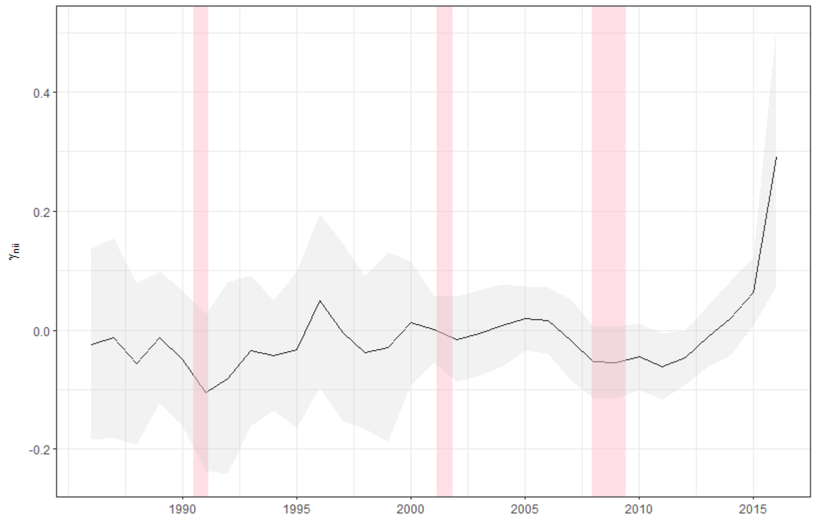


Figure 4: 5-Year Rolling Regressions: The coefficient on $nii_{t-1} \times \Delta i_t$ (γ_{nii})

This figure plots γ_{nii} over time from 5-year rolling regressions based on column 5 in Table 5. The labels on the x-axis corresponds to the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.



9 Appendix: Additional Tables and Figures

Table 6: Descriptive Statistics: Time-Varying Coefficients

This table shows descriptive statistics for the time-varying coefficients based on 5-year rolling regressions reported in section 5.3, and depicted in graphs.

	Mean	**Median**	**Std. Dev.**	**Min**	**Max**	**P25**	**P75**	**N**
β	-0.14	-0.14	0.06	-0.32	-0.04	-0.17	-0.10	31
δ_{liq}	0.43	0.39	0.12	0.26	0.69	0.33	0.52	31
γ_{liq}	0.01	0.01	0.02	-0.02	0.07	-0.00	0.03	31
δ_{size}	-12.66	-10.84	5.71	-24.54	-3.94	-16.66	-7.72	31
δ_{lev}	-0.02	0.07	0.46	-1.12	1.26	-0.18	0.21	31
δ_{nii}	0.25	0.28	0.17	-0.05	0.59	0.13	0.40	31
γ_{size}	-0.01	0.06	0.34	-1.19	0.41	-0.21	0.25	31
γ_{lev}	0.01	-0.01	0.09	-0.17	0.44	-0.03	0.03	31
γ_{nii}	-0.01	-0.02	0.07	-0.11	0.29	-0.05	0.01	31

Figure 5: 5-Year Rolling Regressions: The coefficient of $size$ (δ_{size})

This figure plots δ_{size} over time from 5-year rolling regressions based on column 5 in Table 5. The labels on the x-axis corresponds to the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.

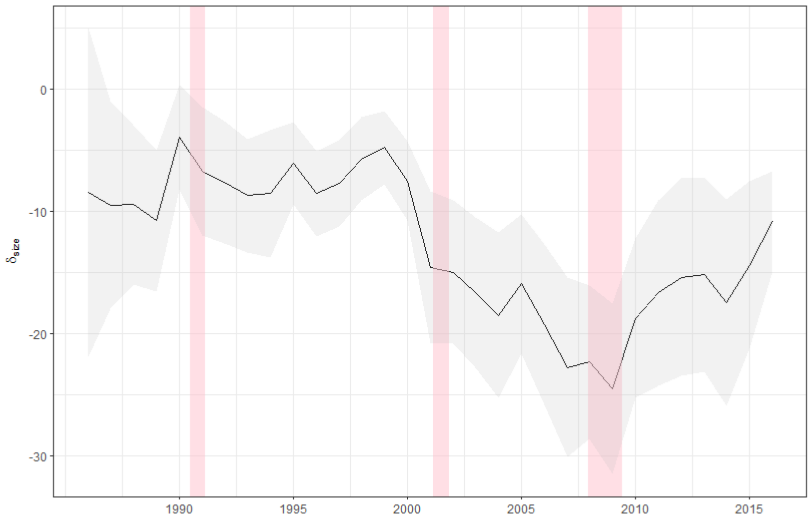


Figure 6: 5-Year Rolling Regressions: The coefficient on $size_{t-1} \times \Delta i_t$ (γ_{size})

This figure plots γ_{size} over time from 5-year rolling regressions based on column 5 in Table 5. The labels on the x-axis corresponds to the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.

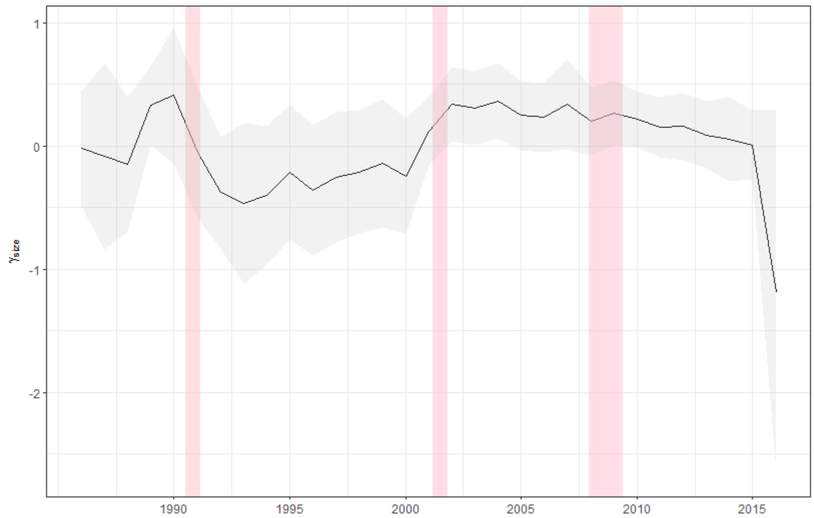


Figure 7: 5-Year Rolling Regressions: The coefficient on *lev* (δ_{lev})

This figure plots δ_{lev} over time from 5-year rolling regressions based on column 5 in Table 5. The x-axis is the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.

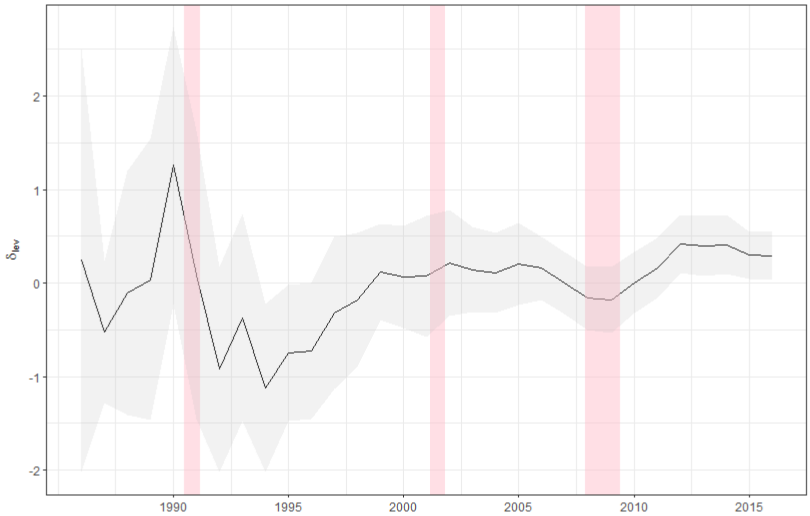


Figure 8: 5-Year Rolling Regressions: The coefficient on $lev_{t-1} \times \Delta i_t$ (γ_{lev})

This figure plots γ_{lev} over time from 5-year rolling regressions based on column 5 in Table 5. The labels on the x-axis corresponds to the end period of the rolling regression window. The grey shaded area indicates 95% confidence interval band and the pink shaded area indicates recessions according to NBER's recession dates.