DNB Working Paper

No 847/November 2025

The Role of Ambiguity in the Monetary Policy Transmissions: Evidence from the European Repo Market

Natalie Kessler and Poramapa Poonpakdee

DeNederlandscheBank

EUROSYSTEEM

The Role of Ambiguity in the Monetary Policy Transmissions: Evidence from the European Repo Market

Natalie Kessler and Poramapa Poonpakdee*

* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 847

November 2025

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

The Role of Ambiguity in the Monetary Policy Transmissions: Evidence from the European Repo Market*

Natalie Kessler† Poramapa Poonpakdee‡

November, 2025

Abstract

We develop a method to measure ambiguity—uncertainty about the distribution of outcomes—in asset markets, using the volatility of the empirical distribution of unpredictable components in transaction prices. For comparison, we measure risk as the volatility of the unpredictable price component itself, following the conventional practice of using the cross-sectional standard deviation. Applying this framework to 22 million secured lending transactions in the EU, we estimate ambiguity and risk perceived by major money market lenders. Unexpected monetary policy tightening raises both measures. Higher ambiguity reduces repo market liquidity by lowering loan volumes and increasing repo rates, thereby amplifying contractionary effects. Higher risk lowers loan volumes but also repo rates, partly dampening contractionary effects. Our results suggest that ambiguity plays a distinct and quantitatively important role in monetary policy transmission that is overlooked when focusing on risk alone.

Key Words: Ambiguity and Risk; Repurchase Agreements; Monetary Policy Transmission; Liquidity Provision

JEL Classification: E52; G24; D43; D86

*We thank our colleagues at De Nederlandsche Bank, in particular Fabio Canova, Tomás Carrera de Souza, Daniel Dimitrov, Iman van Lelyveld, Leonardo Melosi, and Sweder van Wijnbergen. We also appreciate feedback from colleagues at the Finance Department of Vrije Universiteit Amsterdam and the Macro, International, and Labour Economics Department of Maastricht University. Finally, we thank conference audiences for their comments, in particular Fabio Massimo Piersanti for his discussion at the annual workshop of the European System of Central Banks' MPC-Task Force on Banking Analysis for Monetary Policy, and Wasin Siwasarit for his discussion at the Puey Ungphakorn Institute for Economic Research (PIER) Research Workshop. We also thank Stephen Spiegel for his insightfull comments.
The views expressed here are those of the authors and do not necessarily reflect the official positions of De Nederlandsche Bank and the Bank of Thailand.

†Corresponding Author; Vrije Universiteit Amsterdam and De Nederlandsche Bank, n.kessler@dnb.nl

‡Maastricht University (until 2024) and Bank of Thailand, poramapp@bot.or.th

1. Introduction

In economics, uncertainty conventionally refers to situations with an unknown future outcome. More precisely, Knight (1921) decomposes uncertainty into ambiguity[1] and risk. Risk refers to situations where the exact outcome is unknown, but the likelihood of outcomes is known. For example, tossing a fair coin is a risky event with a probability of one-half for heads and tails, respectively. Ambiguity refers to situations where the likelihood of outcomes is unknown, i.e. there is uncertainty over the distribution. For example, tossing a coin, where the exact likelihoods of heads and tails are unknown, is both an ambiguous and risky event.

Throughout the remainder of the paper, we follow Knight (1921) and refer to risk as situations with unknown outcomes and ambiguity as situations with unknown likelihoods of outcomes. We refer to uncertainty when no decomposition has been imposed such that both risk and/or ambiguity may be present. Inspired by Borio and Zhu (2012), the risk-taking channel receives considerable attention in the literature on the transmission of monetary policy. Here, a growing number of papers document both how higher risk dampens the effects of monetary policy on liquidity provision and how large monetary policy shocks impact risk (Aastveit et al., 2017; Bekaert et al., 2013; Drechsler et al., 2018; Neuenkirch and Nöckel, 2018). However, there is a notable absence of attention to ambiguity in monetary policy research, leaving potential complementary effects unexplored. Therefore, we explicitly study the ambiguity transmission channel of monetary policy on liquidity provision.

Our contributions are threefold: First, we develop a novel approach to measure ambiguity and risk in financial markets with heterogeneous contract terms. Second, we document an asymmetric effect of monetary policy shocks on ambiguity and risk: contractionary shocks cause an immediate but short-lived increase in ambiguity and a persistent increase in risk, whereas expansionary shocks reduce both measures. Finally, using a lagged variable approach and a large dataset of 22 million money market transactions, we show that ambiguity has significant contractionary effects on liquidity—above and beyond what can be directly

[1] Ambiguity is sometimes referred to as Knightian uncertainty.

explained by monetary policy shocks and the risk channel.

The main empirical method of measuring ambiguity, developed by Izhakian (2020) to obtain a market-based metric, utilizes the overtime variation in the prices of a publicly traded (homogeneous) asset. Liquidity, however, is sourced predominantly through bilateral transactions in the secured and unsecured money market segments (ECB, 2023b). Common to these and other over-the-counter markets are transaction-level contracts with varying terms. In addition, counterparty pair relationships matter for pricing. Consequently, the prices charged by a single contract issuer do not only vary over time but also cross-sectionally in contract characteristics and counterparties. Therefore, a unified market perception of ambiguity and risk does not exist in such bilateral trading settings, and the need for an evolved measurement approach for ambiguity arises.

To obtain such novel measure, we start with the notion by Jurado et al. (2015) that uncertainty is captured by the unpredictable component in observable economic indicators. Transferring this concept to observed bilateral contracts, uncertainty lies within the price component that is unpredictable given all issuer-observed price determinants. In rich transaction-level datasets, we can take advantage of the heterogeneity in contracts by the same issuer both between and within counterparties to obtain the unpredictable price components: First, fit an adequate (linear) pricing model to an issuer's historic transactions that takes the relevant contract terms, micro and macro controls, and counterparty fixed effects into account. Subsequently, predict the prices of next period's contracts by applying the estimated coefficients to the observed price determinants. Finally, obtain the unpredictable price components, hereafter premia, as the forecasting errors between realized and predicted prices. Applying a rolling-window approach, we obtain a separate set of premia for each issuer in each period observed in the data.

Conditional on having correctly controlled for all issuer-observed price determinants, the resulting premia meet the crucial assumption of underlying homogeneity on an *issuer level*. Therefore, we are able to apply the ambiguity and risk measure proposed by Izhakian (2020) to obtain issuer-perceived ambiguity. Following the original paper, we first obtain an issuer's premia distribution for each period. From there, we measure issuer-perceived ambiguity as the average standard deviation in premia densities across past periods. We measure risk as the within-period standard deviation in premia. If desired, a market index for ambiguity and risk can be computed as a weighted average of the issuer-perceived measures.

In this paper, we apply our measurement approach to the secured euro money market covered by the money market statistical reporting (MMSR). Here, we observe all repurchase agreements (repos) by euro-area significant financial institutions for all trading days between June, 2016 and up to and including December, 2024. We keep the trades where the reporting institution issues the repo, i.e., provides the liquidity and receives the collateral. We extract the repo premia (realized minus predicted return spreads) based on the above specified approach. We calculate ambiguity as the standard deviation in repo premia densities across five days and risk as the standard deviation in premia within a day. As a result, we obtain a daily time-series of the perceived risk and ambiguity for 72 individual issuers.

As a natural next step, we investigate to which extent monetary policy surprises drive repo issuers' ambiguity and risk. For this, we set up a two-stage least squares (2SLS) regression: In the first stage, we instrument the announced changes in the ECB's deposit facility rate with the monetary policy surprise measures developed by Altavilla, Brugnolini, et al. (2019). In the second stage, we obtain local projections by regressing our ambiguity and risk measures on the instrumented rate changes with increasing lags. A contractionary shock implies a more than anticipated rate hike and an expansionary policy shock implies a lower than anticipated rate hike. The second-stage local projections show that contractionary monetary policy shocks significantly increase both ambiguity and risk. The effect on ambiguity is immediate upon the policy announcement but dissipates within two days, whereas the effect on risk emerges one day after the announcement day and persists for a longer period. Expansionary shocks, in contrast, reduce both ambiguity and risk, with larger absolute effects than contractionary shocks.

In the final part of our analysis, we examine the impacts of ambiguity and risk on market liquidity. First, we focus on contract-level lagged-variable regressions to examine how individual repo contract prices and volumes respond to increases in ambiguity and risk. We find that heightened *ambiguity* leads to higher repo rates but has no significant effect on loan volumes, whereas *risk* reduces both lending and prices. These findings are conceptualized within a simple two-equation framework linking prices and quantities to uncertainty. At the contract level, ambiguity primarily affects the price channel, explaining why its impact on loan volumes is negligible. Risk operates mainly through the quantity channel, wherefore the reduction in loan volume dominates and repo rates decrease.

In a second set of lender-level regressions, we examine the effect of ambiguity on total lending volume and borrower concentration (HHI). Here, both risk and ambiguity reduce total lending, but risk additionally encourages diversification across borrowers (reduced HHI). Ambiguity, in contrast, cannot be diversified away and induces a reduction in total borrowing spread equally among all borrowers.

Overall, the evidence supports the presence of both an ambiguity channel and a risk channel in monetary transmission. Ambiguity amplifies contractionary effects, leading lenders to adjust primarily through prices. Risk, on the other hand, impacts liquidity through reduced lending, but partially dampens policy effects with lowered repo rates and higher portfolio diversification. Together, these results highlight an asymmetry in financial responses: price effects dominate under heightened ambiguity, while quantity effects dominate under elevated risk, reflecting the distinct behavioral channels triggered by these two forms of uncertainty. Effective policy design should therefore aim to reduce ambiguity while managing risk, ensuring that monetary actions are both well understood and credibly transmitted to financial markets.

Literature Review As mentioned in the introduction, ambiguity is by no means a new concept and dates back to Knight (1921). Over the course of time, ambiguity has received repeated attention, especially in decision theories (Ellsberg, 1961; Gilboa and Schmeidler, 1989), but also, for example, in prospect theory (Kahneman and Tversky, 1979) or experimental research (Ahn et al., 2014; Bossaerts et al., 2010).[2] More recently, the formal introduction of the volatility of probabilities as an empirically-applicable measure of ambiguity by Izhakian (2020) sparked a small but growing ambiguity literature in asset pricing. Here, the aforementioned concept of ambiguity by Izhakian (2020) has been applied to equity markets by Brenner and Izhakian (2022) and Coiculescu et al. (2023), to standardized options by Chen and Han (2023), and exchange rates by Karahan and Soykök (2022).

Common to the existing works on measuring ambiguity is that the underlying asset is homogeneous across all trades, wherefore ambiguity can be identified through price variations over time. Our study adds to the literature by specifically focusing on measuring ambiguity in asset markets with heterogeneous contract terms in the cross section of transactions. To achieve this, we build upon the notion by Jurado et al. (2015) that uncertainty is associated with the variation in the unpredictable price components rather than observed prices. We show how econometric analysis allows to extract unpredictable price premia, the variation in bilateral transaction prices *not* driven by custom contract terms and counterparty pair relationship. Subsequently, we describe how to utilize the measurement approach by Izhakian (2020) to decompose the variance in the unpredictable price premia in ambiguity and risk.

With our application in the euro area repo market, we demonstrate not only how our concept can be put to practice but also how it can provide a foundation for further analysis of economic and/or financial policies. In this paper in particular, we study how monetary policy influences perceived ambiguity and risk in the repo market, and how risk and ambiguity in return impacts the liquidity provision in the repo market.

On the intersection between uncertainty and monetary policy, the vast majority of existing papers study the impact of monetary policy uncertainty on real choices, such as investment and production (Greenspan, 2004; Mueller et al., 2017), while others analyze the optimal policy response under uncertainty from the central bank's perspective (Craine, 1979;

[2]See Etner et al. (2012) for a detailed review of the literature on ambiguity in decision theory and related fields.

Wieland, 2000). In contrast, we study how monetary policy influences uncertainty, aligning with Bekaert et al. (2013) and Bauer et al. (2022). The former uses the VIX to identify uncertainty[3] and finds that expansionary policy marginally lowers uncertainty; the latter derives policy uncertainty from Eurodollar options and shows that forward guidance and expansionary policy reduce it. We extend this literature by decomposing uncertainty into risk and ambiguity and by constructing our measure from the individual lender's perspective rather than a market-average perspective, enabling us to capture heterogeneity in perceived uncertainty across financial institutions.

Additionally, we document that such responses have real effects on the monetary policy transmission via the repo market. A complete review of the vast literature on monetary policy transmission channels is beyond the scope of this paper, and the interested reader is kindly referred to recent papers by Holm et al. (2021) or Miranda-Agrippino and Ricco (2021). Conceptionally closest to our paper is the study by Aastveit et al. (2017), who document that high macroeconomic, economic policy and stock market uncertainty dampen the effect of monetary policy on especially GDP growth. Instead taking a micro-econometric stance, we focus on the ambiguity transmission channel of monetary policy for individual lenders' liquidity provision and find similar dampening effects. We are thus able to establish an additional explanation for the sluggish response to rate hikes in repo beyond the market power argument brought forward by Eisenschmidt et al. (2024).

This paper is structured as follows. Section 2 and 3 describe our conceptual framework and its application on the repo market. Section 4 presents the effects of monetary policy shocks on ambiguity and risk. Section 5 discusses the impacts of ambiguity and risk on the liquidity provision. Finally, Section 7 gives a brief conclusion.

[3]Bekaert et al. (2013) decompose the VIX into expected volatility—referred to as uncertainty in their paper—and a variance premium, interpreted as risk aversion.

2. Conceptual Framework

It is the task of this section to: [1] discuss the two complementary concepts by Izhakian (2020) and Jurado et al. (2015) on how to measure market perceived ambiguity and macroeconomic uncertainty, respectively; and [2] to unify them in a single approach that allows to estimate risk and ambiguity in the transaction level data with heterogeneous contract terms.

2.1. Market Perceived Ambiguity

Following Knight (1921), utility optimization under risk refers to decision making in situations where the exact outcome is unknown but the likelihoods of outcomes are known. Utility optimization under ambiguity, on the other hand, refers to decision making under unknown outcome likelihoods.[4] Izhakian (2017) unifies decision making under both uncertainty aspects in his expected utility with uncertain probabilities (EUUP) framework.

Izhakian (2017) defines expected utility under ambiguity and risk as follows[5]:

$$E\big(U(\mathbf{X})\big) = \sum_i \beta_i \sum_j p_{ij} U(x_j),$$

where $E(\cdot)$ is the expectations operator, $U(\cdot)$ is the von Neumann-Morgenstern utility function, $\mathbf{X}$ the set of outcomes, i is an index of possible scenarios, β_i is the likelihood of scenario i, j is an index of possible outcomes x_j in outcome set $\mathbf{X}$, and p_{ij} is the probability for outcome x_j in scenario i.

Conventionally, risk is measured by the volatility σ_i of outcomes x_j within a given scenario i:

$$\sigma_i(\mathbf{X}) = \sqrt{\sum_j p_{ij}\big(x_j - E(\mathbf{X} \mid i)\big)},$$

[4]The concept of ambiguity has been further expanded by Hansen and Sargent (2001) into two distinct types. The first type is characterized by uncertainty surrounding the optimal set of parameters for a given model, simply referred to as "ambiguity." The second type, known as model misspecification, refers to uncertainty surrounding the structure of the model itself. In our study, we do not differentiate between the two forms, but rather consider ambiguity as uncertainty surrounding the probability distribution.

[5]For the ease of reading, we discretize the EUUP model.

where the expected value of a given scenario i is:

$$E(\mathbf{X} \mid i) = \sum_j p_{ij} x_j.$$

Complementary, Izhakian (2020) derives a theoretically founded measure of ambiguity from the EUUP framework that is risk-independent, outcome-independent (up to a state space partition), preference-independent[6] and empirically applicable. Formally, the degree of ambiguity Υ can be measured as the expected volatility in the probabilities across potential scenarios:

$$\Upsilon(\mathbf{X}) = \sqrt{\sum_j E\Big(p_i\left(x_j\right) \mid j\Big) Var\Big(p_i\left(x_j\right) \mid j\Big)},$$

where for each outcome state j:

$$\begin{aligned} E\Big(p_i\left(x_j\right) \mid j\Big) &= \sum_i \beta_i p_i(x_j), \\ Var\Big(p_i\left(x_j\right) \mid j\Big) &= \sum_i \beta_i \Big(p_i\left(x_j\right) - E\Big(p_i\left(x_j\right)\Big)\Big)^2. \end{aligned}$$

Crucially, both ambiguity and risk measures assume that all observed outcomes within a scenario i are independent draws from the same distribution. To empirically measure ambiguity and risk, we therefore require a dataset in which outcomes can reasonably be assumed to be unpredictable draws from some underlying distribution. Existing applications are thus largely limited to publicly traded, homogeneous assets whose outcomes are difficult to forecast, such as stock returns (Coiculescu et al., 2023) and exchange rates (Karahan and Soykök, 2022). These measures capture *market-perceived* ambiguity. Instead, our study stands as the first to measure *individual traders' perceived* ambiguity from transaction-level data that covers heterogeneous assets. To achieve this, we adapt the above defined ambiguity and risk measures by partially rely on insights derived in the empirical literature on measuring

[6] Fu et al. (2023) commented on the issue of separation of ambiguity and its preferences. Izhakian (2024) has replied that their comments are incompatible with the Izhakian (2020)'s ambiguity measure.

macroeconomic uncertainty.

2.2. Macroeconomic Uncertainty

Jurado et al. (2015) highlight that much of the variation in existing empirical proxies for uncertainty is not truly driven by uncertainty but predictable shifts. To avoid over-estimating uncertainty, the authors propose a direct and time-varying econometric estimate of macroeconomic uncertainty based on forecasting errors. Intuitively, they emphasize a focus shift from volatility in observed outcomes to volatility in the unpredictable component of observed outcomes. With a slight adjustment of the original notation, let $y_{n,t+h}$ denote the realized value y of an outcome series n at time $t+h$, i.e. h periods ahead. Further, denote the information set at time t with I_t. Then the H-period ahead return uncertainty $\mathcal{U}_{n,t+H}$ is the volatility in forecast errors between observed value $y_{n,t+h}$ and expected value $E(y_{n,t+h} \mid I_t)$ over H periods:

$$\mathcal{U}_{n,t+H} = \sqrt{\frac{1}{H} \sum_{h=1}^{H} \Big(y_{n,t+h} - E\left(y_{n,t+h} \mid I_t \right) \Big)^2}$$

Subsequently, a macroeconomic uncertainty index for period $t+H$ can be obtained as a weighted average across N different data series:

$$\mathcal{U}_{t+H} = \sum_{n=1}^{N} w_n \mathcal{U}_{n,t+H}. \tag{1}$$

Notice that the approach by Jurado et al. (2015) utilizes both variation in the time and the cross-sectional dimension to measure uncertainty. Yet, it lacks the decomposition of uncertainty into risk and ambiguity.

2.3. Measuring Ambiguity and Risk in Transaction Data

In this section, we highlight how in particular the cross-sectional dimension can be explored to measure risk and ambiguity from bilateral transactions.

Unpredictable Price Premia We start by identifying the unpredictable premium in the observed transaction price. Intuitively, this premium represents the excess price requested by the security issuer—and paid by the buyer—beyond the compensation for the expected return, analogous to the bond premium defined by Gilchrist and Zakrajšek (2012). The specification of the pricing model used to determine the expected return is therefore crucial for extracting the unpredictable price premia.

Let superscript s denote a unique security identifier of a transaction between issuer i and buyer b at time t. Further, let $P^i_{s,t}$ denote the price of transaction s charged by issuer i at time t. Finally, let $\mathbf{B}^i_{b,t}$ denote the set of buyer characteristics and let the set $\mathbf{O}^i_{s,t}$ denote other issuer-known variables such as contract terms, macroeconomic conditions and other publicly available information relevant for pricing.

Assumption 1 (Full Information and Observability)**.** *The combined set* $\{\mathbf{B}^i_{b,t}, \mathbf{O}^i_{s,t}\}$ *exhausts the issuer's information set at time t, and all its elements are observable (or measurable via known proxies).*

Further, we assume that for a generic forecast period $t+f$, the observed transaction price $P^i_{s,t+f}$ is the sum of an issuer-specific price prediction function $\mathcal{P}^i_t(\cdot)$, and an unpredictable premium $u^i_{s,t+f}$. The pricing function $\mathcal{P}^i_t(\cdot)$ is determined using information available to the issuer i at period t but evaluated at $t+f$ using updated inputs $\mathbf{B}^i_{b,t+f}$ and $\mathbf{O}^i_{s,t+f}$.

Assumption 2 (Additive Separability)**.** *The security transaction price* $P^i_{s,t+f}$ *is additively separable in a price prediction function* $\mathcal{P}^i_t(\cdot)$*, determined at* t *and evaluated on observables* $\mathbf{B}^i_{b,t+f}$ *and* $\mathbf{O}^i_{s,t+f}$ *at* $t+f$*, and a price premium* $u^i_{s,t+f}$*:*

$$P^i_{s,t+f} = \mathcal{P}^i_t(\mathbf{B}^i_{b,t+f}, \mathbf{O}^i_{s,t+f}) + u^i_{s,t+f},$$

$$\textit{where } \mathcal{P}^i_t : \mathbf{B}^i_{b,t+f} \times \mathbf{O}^i_{s,t+f} \mapsto \mathbb{R}.$$

The exact pricing model may only be known to the issuer i. Assumption 3 ensures the pricing function is estimable from the finite data window W, and that the premium $u^i_{s,t+f}$

is mean-independent of observables conditional on $\mathbf{B}^i_{b,t+f}$ and $\mathbf{O}^i_{s,t+f}$.

Assumption 3 (Estimatability and Orthogonality)**.** *Using data available up to period t, there exists an estimable pricing function $\widehat{\mathcal{P}}^i_t$ based on $\{P^i_{s,\tau}, \mathbf{B}^i_{b,\tau}, \mathbf{O}^i_{s,\tau}\}^t_{\tau=t-W}$ such that, for any forecast horizon $f \in \{1, \ldots, F\}$,*

$$\mathbb{E}\Big[u^i_{s,t+f} \,\Big|\, \mathbf{B}^i_{b,t+f}, \mathbf{O}^i_{s,t+f}\Big] = 0.$$

It follows from Assumptions 1 through 3 that the unpredictable premium can be estimated as the residual between the observed price and the predicted price, where the latter is obtained from estimating the pricing model on historic data and subsequently fitting it to the observable issuer information.

***Observation* 1** (Premium Estimation)**.** *Under Assumptions 1, 2 and 3, the unpredictable premium $u^i_{s,t+f}$ can be estimated as the residual between the observed price $P^i_{s,t+f}$ and the predicted price $\hat{P}^i_{s,t+f}$:*

$$\begin{aligned} \hat{u}^i_{s,t+f} = P^i_{s,t+f} - \hat{P}^i_{s,t+f} \quad \forall s \ \textit{s.t.}\ f \in \{1, \ldots, F\}, \\ \textit{where}\ \hat{P}^i_{s,t+f} = \widehat{\mathcal{P}}^i_t(\mathbf{B}^i_{b,t+f}, \mathbf{O}^i_{s,t+f}). \end{aligned}$$

Assumption 1 is a data requirement, while Assumptions 2 and 3 place very broad restrictions on the pricing function to be estimated. Many classes of estimation models are thus compatible with Assumptions 2 and 3. For identification in this paper, we impose two additional assumptions: the pricing model is linear; and buyer-specific characteristics $\mathbf{B}^i_{b,t}$ are time-invariant in a (potentially narrow) time window. If these two additional assumptions are considered unnecessary in a specific setting, they may be disregarded.

Assumption 4 (Linearity)**.** *The issuer's pricing function $\mathcal{P}^i_t(\mathbf{B}^i_{b,t+f}, \mathbf{O}^i_{s,t+f})$ is linear in inputs $\mathbf{B}^i_{b,t+f}$ and $\mathbf{O}^i_{s,t+f}$.*

Assumption 4 on linearity ensures that we can utilize ordinary least squares (OLS) estimators to extract the price premium. Assumption 5 on time-invariance is necessary in settings where we lack detailed panel data on buyer characteristics at each date. Without direct observations, we cannot flexibly model buyer heterogeneity over time. However, this is not necessary if buyer characteristics can reasonably be assumed to be time-invariant over the estimation and prediction window. Were comprehensive buyer data is available, Assumption 5 can be disregarded.

Assumption 5 (Time-Invariance)**.** *For all periods t within the timeframe $t-W$ to $t+F$, buyer characteristics are constant:*

$$\mathbf{B}^i_{b,t} = \mathbf{B}^i_b \quad \forall t \in \{t-W, \dots, t-w, \dots, t, \dots, t+f, \dots, t+F\} \tag{2}$$

If the model is linear in its components (Assumption 4) and buyer-specific characteristics are persistent (Assumption 5), these characteristics can be absorbed through buyer fixed effects in an OLS estimation. Hence, a standard buyer fixed effects regression over the periods $t-W$ to t recovers the issuer's pricing function.

***Observation* 2** (Fixed-Effects Estimation)**.** *Under Assumptions 4 and 5, the issuer-specific OLS regression with buyer fixed effects estimates the pricing function $\mathcal{P}^i_t(\mathbf{B}^i_{s,t-w}, \mathbf{O}^i_{s,t-w})$:*

$$P^i_{s,t-w} = \underbrace{\alpha^i_b + \mathbf{O}^i_{s,t-w}\boldsymbol{\beta}^i_t}_{\mathcal{P}^i_t(\cdot)} + \epsilon^i_{s,t-w} \qquad \forall s \ s.t. \ w \in \{0, \dots, W\}$$

where α^i_b denotes the buyer fixed effect and $\boldsymbol{\beta}^i_t$ is the vector of coefficients.

Subsequently, the estimated coefficients from Observation 2 can be used to predict the price $\hat{P}^i_{s,t+f}$ for all securities s in the forecasting window $t+1$ to $t+F$. Finally, the price premium can be extracted as the residual between the observed and predicted price.

***Observation* 3** (Residual Extraction)**.** *Following Assumptions 1 through 5, the price premium is captured by the residual between the observed price and a fixed-effects based price forecast:*

$$\hat{u}^i_{s,t+f} = P^i_{s,t+f} - \left(\hat{\alpha}_b + \mathbf{O}^i_{s,t+f}\hat{\boldsymbol{\beta}}^i\right) \qquad \forall s \ s.t. \ f \in \{1, \dots, F\}.$$

The above unpredictable premium of issuer i is the transaction level equivalent of the unforecastable component in one macroeconomic variable, whose variance Jurado et al. (2015) associate with uncertainty. However, instead of following their approach to obtain an issuer i's uncertainty index, we suggest how to decompose uncertainty into risk and ambiguity using Izhakian (2020)'s method.

Risk and Ambiguity Decomposition For the risk and ambiguity decomposition, let $\hat{U}_t^i$ denote the set containing all unpredictable premia $\hat{u}_{s,t}^i$ for securities issued by issuer i at time t as defined in Observation 1 above. Then following Izhakian (2020), we define risk as the cross-sectional variation within the set $\hat{U}_t^i$.

Definition 1. *Risk $\mathcal{R}_t^i$ is measured by the standard deviation of all premia $\hat{u}_{s,t}^i$ in superset $\hat{U}_t^i$:*

$$\mathcal{R}_t^i = \sqrt{\frac{1}{S}\sum_{s=1}^{S}(\hat{u}_{s,t}^i - E(\hat{u}_{s,t}^i))^2}$$

where

$$E(\hat{u}_s^i) = \frac{1}{S}\sum_{s=1}^{S}\hat{u}_{s,t}^i.$$

Following Izhakian (2020), ambiguity is defined as the expected volatility of the probabilities of $u_{s,t}^i$. To measure this, we must first determine the number N and width Δ of equally spaced bins that cover a reasonable range of $\hat{u}_s^i$. For each bin n and period t, the bin density $\hat{d}_{n,t}$ is calculated as the number of price premia $\hat{u}_s^i$ falling into that bin divided by the total number of premia in set $\hat{U}_s^i$:

$$\hat{d}_{n,t}^i = \frac{1}{S}\sum_{s=1}^{S}\mathbb{1}\{\hat{u}_{s,t}^i \in n\}.$$

Next, one can obtain the average density $E(\hat{d}_{n,t}^i)$ and density variance $Var(\hat{d}_{n,t}^i)$ for each bin n across a chosen number $A > 1$ of past periods:[7]

[7] Note that the below equations assume an equal weight of each density within calculation window A as proposed by Izhakian (2020). Theoretically, one may use a non-equally weighted average/variance instead if information about appropriate weights are available.

$$
\begin{aligned}
E\left(\hat{d}_{n,t-a}\right) =& \frac{1}{A}\sum_{a=0}^{A}\hat{d}^{i}_{n,t-a} \\
Var\left(\hat{d}^{i}_{n,t-a}\right) =& \frac{1}{A}\sum_{a=0}^{A}\left(\hat{d}^{i}_{n,t-a} - E\left(\hat{d}^{i}_{n,t}\right)\right)^{2}
\end{aligned}
$$

Finally, issuer-perceived ambiguity $\mathcal{A}^{i}_{t}$ is measured as the average volatility in density across all bins weighed by their respective expected density:

$$
\mathcal{A}^{i}_{t} = \sqrt{\frac{1}{\sqrt{\Delta(1-\Delta)}}\sum_{n=1}^{N} E\left(\hat{d}^{i}_{n,t-a}\right) Var\left(\hat{d}^{i}_{n,t-a}\right)}.
$$

Here, dividing by the square root of $\Delta(1-\Delta)$ is a variation of Sheperd's correction and suggested by Izhakian (2020) to minimize the effect of bin width Δ. Definition 2, below, summarizes the computation of the ambiguity measure.

Definition 2. *For a given number N of bins with width Δ, and the sets $\{\hat{U}^{i}_{t}\}^{t}_{t-A}$ containing all price premia from the past A periods, an issuer's perceived ambiguity $\mathcal{A}^{i}_{t}$ is measured by as weighted average standard deviation in bin density:*

$$
\mathcal{A}^{i}_{t} = \sqrt{\frac{1}{\sqrt{\Delta(1-\Delta)}}\sum_{n=1}^{N} E\left(\hat{d}^{i}_{n,t-a}\right) Var\left(\hat{d}^{i}_{n,t-a}\right)}
$$

where

$$
\begin{aligned}
\hat{d}^{i}_{n,t-a} =& \frac{1}{|\hat{U}^{i}_{t-a}|}\sum_{s}\mathbb{1}\{\hat{u}^{i}_{s,t-a} \in n\} \\
E\left(\hat{d}^{i}_{n,t-a}\right) =& \frac{1}{A}\sum_{a=0}^{A}\hat{d}^{i}_{n,t-a} \\
Var\left(\hat{d}^{i}_{n,t-a}\right) =& \frac{1}{A}\sum_{a=0}^{A}\left(\hat{d}^{i}_{n,t-a} - E\left(\hat{d}^{i}_{n,t-a}\right)\right)^{2}.
\end{aligned}
$$

In the next section, we apply the proposed framework to the EU-based repo market.

3. Measuring Ambiguity in the Repo Market

This section outlines the application of the theoretical framework discussed in Section 2 to the European repo market. We provide a description of the data utilized, along with a presentation of its summary statistics. Subsequently, the estimation of repo premia is elaborated, followed by the construction of ambiguity and risk indices. Finally, we briefly explain the measurement of monetary policy shocks, which will be further explored in Section 4.

3.1. Data Description

We use the Money Market Statistical Reporting data from the European Central Bank (ECB) as our primary data source. This dataset contains all repo transactions that are conducted by the 72 largest traders between 2016 to 2024. For each repo, a range of information can be observed, such as the identities of the counterparty pair, the nominal values of transaction size, the interest rate, the security used as collateral, the haircut, and the maturity (ECB, 2023b).[8] From the raw data, we exclude the small percentage of long-term repos, transactions with missing relevant variables, as well transactions falling in the 1st and 99th percentile in loan volume and/or repo rate.

Additionally, we use the ECB's deposit facility rate (DFR) as our main measure of monetary policy — the relevant macro-economic condition for the repo market. Figure 1 displays the deposit facility rate over time. We compute the repo spread of each contract as the difference between the contracted rate and the deposit facility rate as depicted in Figure 2. Table 1 presents final sample summary statistics for the most relevant variables and selected aggregates.

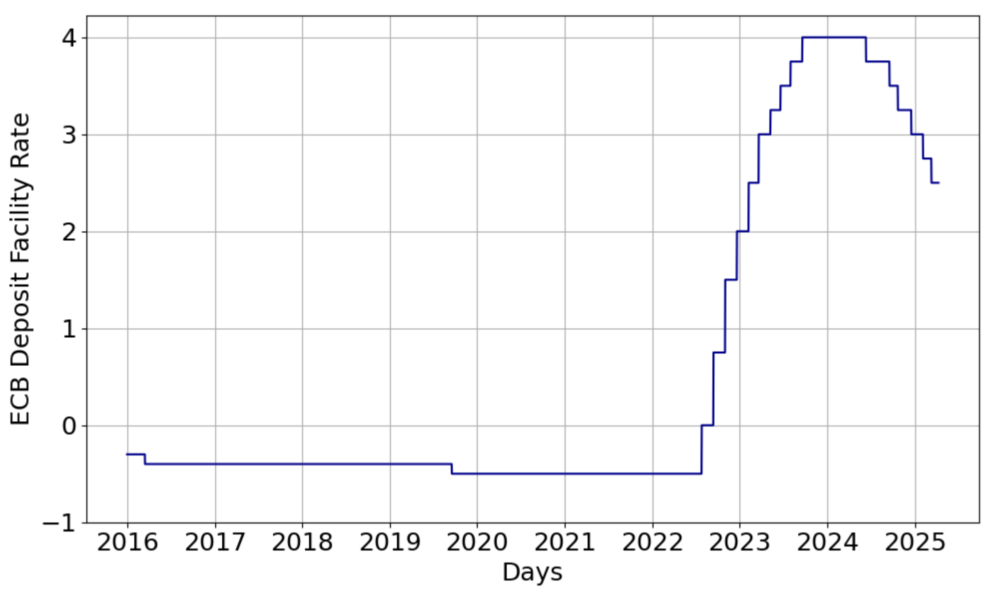
[8] See ECB (2023a) for a detailed list of available fields.

Table 1: Summary Statistics

Continuous Variables	Mean	SD	P10	P90		Obs.
Repo rate	0.81	1.92	-0.85	3.74		22,388,612
Repo spread	-0.24	0.42	-0.60	0.02		22,388,612
Nominal loan value (€ mn)	16.92	27.57	0.55	48.93		22,388,612
Daily transactions per borrower	14.71	22.96	2.17	28.07		52,381
Categorical Variables					%	
Rate Type						
Fixed Rate					90.11	20,173,275
Variable Rate + Spread					9.89	2,215,337
Maturity Bucket						
Overnight (O/N)					45.62	10,213,133
Spot next (S/N) and tomorrow next (T/N)					54.38	12,175,479
Collateral Issuer Rating						
High grade (HG)					48.33	10,821,138
Medium to low grade (MLG)					47.98	10,742,022
Other (special grade etc.)					3.69	825,452

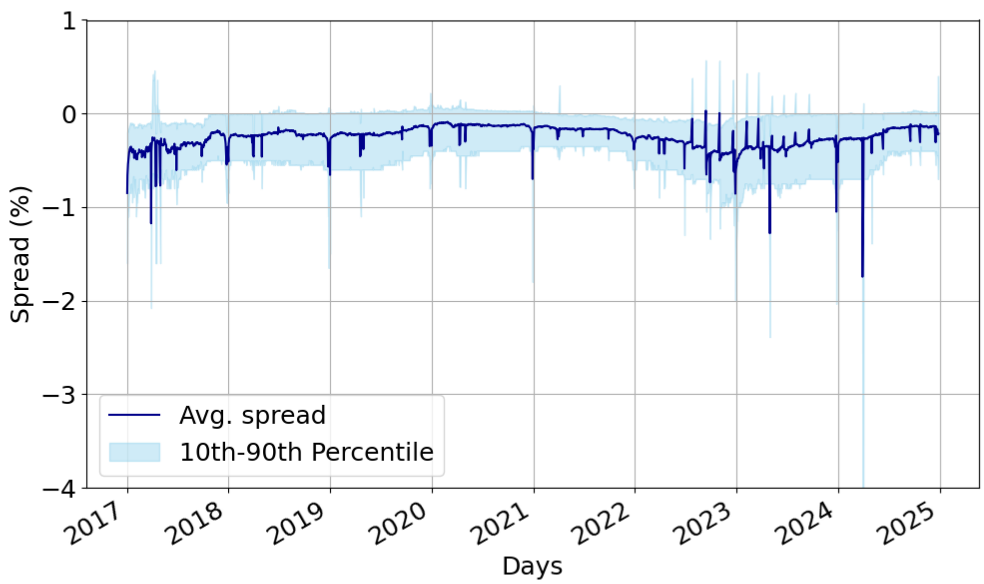
Note: The table displays the summary statistics of the most important contract terms as reported in the MMSR data. There are 72 lenders in the sample.

Figure 1: ECB's Deposit Facility Rate from 2016 to 2025



Note: The figure displays the ECB's effective deposit facility rate at which banks may deposit overnight with the Eurosystem (ECB, 2025).

Figure 2: Spread between Repo Rate and Effective Deposit Facility Rate



Note: The figure displays the daily average spread across all transactions (dark line) and the 10th and 90th percentile (shaded are). The average spread is consistently below zero, implying most contracts charge a rate below the DFR.

3.2. Estimating Repo Premia (Unexplainable Components)

Our focus is on the repo rate premium received by money lenders who are exposed to uncertainty when loaning money to other counterparties. This premium is the interest the borrower pays the lender as compensation for the increased uncertainty associated with the repo transaction such as counterparty default, collateral price fluctuations and (D'Amico and Pancost, 2022). In essence, the repo rate premium serves as an indicator of the risk and ambiguity perceived by lenders in the repo market. In our analysis, we consider the repo premium to be the residual portion of the repo rate that is not accounted for in the pricing model utilized by lenders.

To construct the repo pricing model, we employ OLS regressions using rolling windows. This approach involves first calculating the repo spread by subtracting ECB's effective deposit facility rate from repo rates, thereby removing the direct influence of monetary policy on repo rates. Subsequently, we conduct regressions using repo spreads as the dependent variable and all relevant information on repo contracts utilized by lenders as independent variables. These variables include characteristics of the repo contract and information on the lender and borrower. The repo pricing model of each lender i is:

$$
\begin{aligned}
Spread_{s,b,t} = {} & \beta_1 Log\ Loan\ Volume_{s,b,t} \\
& + \beta_2 Collateral\ Haircut_{s,b,t} \\
& + \beta_3 Nr.\ of\ Borrowers_t \\
& + \beta_4 Nr.\ of\ Borrower\ Contracts_{b,t}\ /Nr.\ of\ Total\ Contracts_t \\
& + \beta_5 Last\ Trading\ Day\ of\ Month_t \\
& + \alpha_b + \alpha_c + \alpha_{m\times r} + \alpha_w + u_{s,b,t},
\end{aligned}
\tag{3}
$$

where s indexes transactions, b indexes borrowers, and t indexes trading days; α_b represents borrower fixed effects, α_c represents collateral (ISIN) fixed effects, $\alpha_{m\times r}$ represents maturity bucket times announced rate fixed effects, and α_w represents weekday fixed effects; and $u_{s,b,t}$

denotes the error term.

To comply with confidentiality regulations, we do not report the results of individual rolling window regressions. Table 2 presents estimates from a pooled regression combining the full sample and all lenders. To account for cross-sectional differences, we include counterparty pair fixed effects in place of borrower fixed effects, and to account for the longer time horizon, we additionally include month-by-year fixed effects.

Table 2: Regressions Result of Repo Spread from the Full Sample

	$\text{Spread}_{s,i,b,t}$ (%): Repo $\text{Rate}_{s,i,b,t}$ minus DFR_t
Log Loan $\text{Volume}_{s,i,b,t}$	0.0106***
	(0.0023)
Collateral $\text{Haircut}_{s,i,b,t}$ (%)	-1.90E-09***
	(3.96E-10)
Nr. of $\text{Borrowers}_{i,t}$	0.0007***
	(0.0001)
Nr. of Pair $\text{Contracts}_{i,b,t}$ / Nr. of Lender $\text{Contracts}_{i,t}$	0.0659**
	(0.0276)
Last Trading Day of Month_t	0.0050**
	(0.0021)
Tuesday_t	-0.002**
	(0.0008)
Wednesday_t	-0.0099***
	(0.0015)
Thursday_t	-0.0068***
	(0.0013)
Friday_t	-0.0057***
	(0.0009)
Counterparty Pair FE	Y
Collateral FE	Y
Maturity Bucket × Announced DRF FE	Y
Month × Year FE	Y
Constant	Y
Adj. R-squared	0.517
Observations	22,388,612

Note: Clustered Standard errors on the lender level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table displays the panel regression on the whole sample, where the repo spread of each transaction s entered between issuer i and borrower b on date t is regressed on several contract terms as well as a rich set of fixed effects.

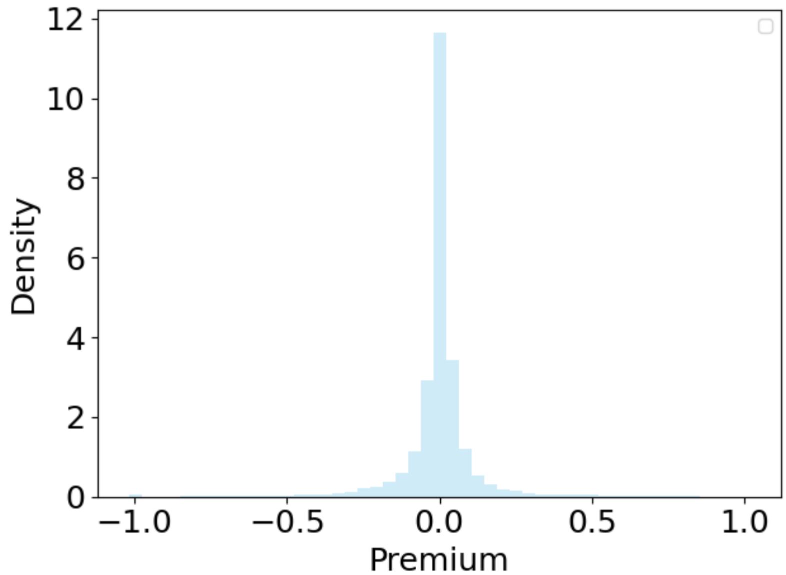
Table 2 indicates that larger transaction sizes are associated with higher spreads—specifically, a 1% increase in principal value raises the spread by approximately 0.0106%. In contrast, higher collateral haircuts reduce spreads, with a coefficient of -1.90E-09,indicating a negligible economic effect. Each additional borrower increases the spread by 0.0007%, suggesting that lenders can charge higher rates when they have more borrowers to lend to. Moreover, if a single borrower engages in more contracts, the spread increases by 0.0657%. Seasonal patterns are also evident: the spread is 0.0051% higher on the last day of the month, while lending on days other than Friday reduces the spread. Overall, these results indicate that lenders incorporate contract characteristics, borrower concentration, and predictable seasonal patterns into their repo rate pricing.

The repo premium is determined by calculating the difference between the observed repo spread and the predicted repo spread derived from a repo pricing model. It is assumed that the lender regularly updates their pricing model on a weekly basis, utilizing data from the preceding four weeks. For example, in order to obtain the predicted repo spreads of Lender i for the first week of April, a regression analysis is conducted utilizing Lender i's data from the first to fourth weeks of March, and the resulting coefficients are leveraged to predict the repo spreads for the first week of April.

$$\widehat{Premium}_{s,i,b,t} = Spread_{s,i,b,t} - \widehat{Spread}_{s,i,b,t} \tag{4}$$

A very small fraction of the 21,960 individual regressions suffer from from multicollinearity concerns due to few observations in a particular week. To avoid spurious predictions disproportionately influencing our results, we truncate the extreme predictions by dropping the 0.1% and 99.9% quantiles. Figure 3 displays the estimated premia used for further analysis.

Figure 3: Histogram of Repo Premia



Note: The figure displays the histogram of premia as obtained from (5) above. The premia below −1 are added to the first bin. The unconditional mean of premia is 0.01 and the standard deviation is 0.14.

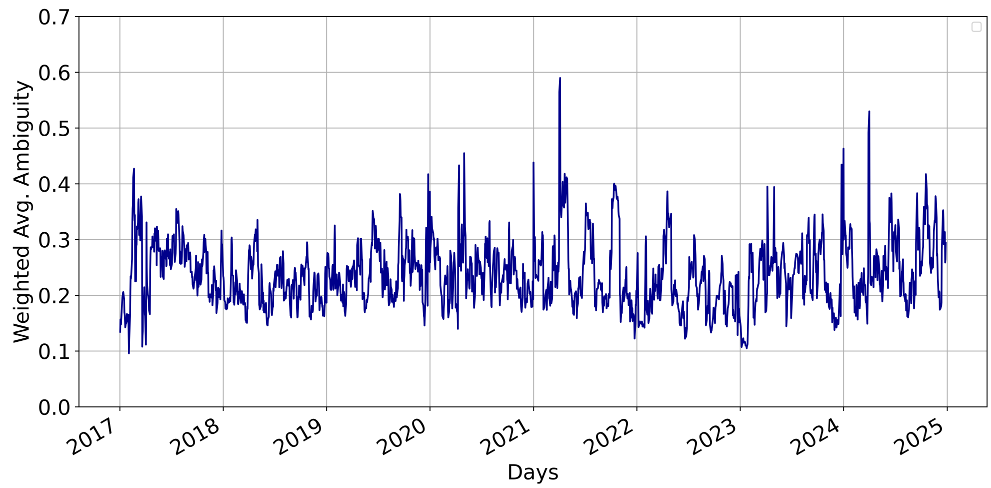
3.3. Ambiguity and Risk from the Repo Rate Premium

We measure the risk and ambiguity using the repo rate premium received by cash lenders in the European repo market. Specifically, a higher variance of the premia indicates that the lender is facing a higher level of risk, whereas a change in the distribution of the premiums implies that the lender views the repo market as being characterized by greater ambiguity.

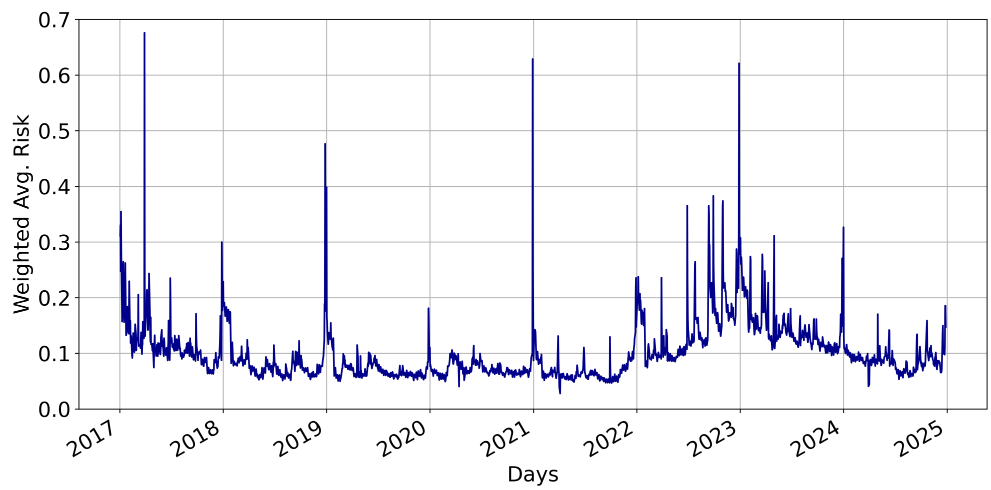
Figure 4 depicts the average ambiguity and risk weighted by the daily loan values of money lenders. Ambiguity is more volatile than risk, with an average standard deviation across lenders of 0.19 compared to 0.06 for risk. The two indicators do not necessarily move together; in fact their correlation is -0.28 based on daily averages. Risk is positively correlated with the EURO STOXX 50 Volatility Index (0.05), while ambiguity is negatively correlated (-0.06); both correlations are statistically significant. To illustrate the dynamics of ambiguity and risk, we focus on developments between 2019 and 2022. At the beginning of 2019, ambiguity averaged around 0.2, rising above 0.4 during the US–China trade war. After a brief decline at the end of 2019, ambiguity surged again amid the onset of the COVID-

19 crisis. By contrast, risk appears less sensitive to these macroeconomic events, instead increasing during the policy normalization phase in 2022 and exhibiting occasional year-end spikes associated with lower transaction volumes. Overall, these results demonstrate the importance of considering ambiguity and risk as separate, yet interconnected factors in analyzing repo markets

Figure 4: Average Ambiguity and Risk



(a) Weighted Average Ambiguity



(b) Weighted Average Risk

Note: Figures (a) and (b) display the lenders' daily loan-value weighted average ambiguity and risk, respectivly.

3.4. *Monetary Policy Shocks*

We follow the established method by Altavilla, Brugnolini, et al. (2019) and Altavilla, Burlon, et al. (2022) to obtain shocks in monetary policy of the euro area. We instrument our announced DFR changes with the four monetary policy surprises—target, quantitative easing, timing, and forward guidance—derived in Altavilla, Brugnolini, et al. (2019):[9]

$$\Delta DFR_t = \text{Target}_t + \text{Quantitative easing}_t + \text{Timing}_t + \text{Forward Guidance}_t + \epsilon_t, \quad (5)$$

where ΔDFR_t denotes the change in the announced policy rate (deposit facility rate).

Throughout the rest of the paper, we refer to the fitted values of the above regression as our monetary policy shock $\Delta\widehat{DFR}_t$.

4. The Impact of Monetary Policy on Ambiguity

In this section, we study the impact of monetary policy on the perceptions of ambiguity and risk held by money lenders. We obtain impulse responses following the approach by Altavilla, Burlon, et al. (2022): We regress the change in ambiguity/risk perceived by lender i between times t and $t+h$, generically denoted $\Delta\mathcal{U}_{i,t\to t+h}$, on the monetary policy shock $\Delta\widehat{DFR}_t$ and a matrix $\mathbf{X}_{t,i}$ of relevant control variables.[10]

We estimate two local projection specifications. The first captures the total impact of monetary policy shocks:

$$\Delta\mathcal{U}_{i,t\to t+h} = \alpha_{i,h} + \beta_h \Delta\widehat{DFR}_t + \mathbf{X}_{i,t}\gamma_{\mathbf{h}} + \epsilon_{i,t+h}. \quad (6)$$

[9] We use the R-package *hfdshocks* provided by Baumgaertner (2025).

[10] The model takes into account the following control variables: avg. number of contracts per counterparty, number of counter parties, total log total losn volume, and weekday, month, and year FE. Additionally, the credit rating of the lender was explored but ultimately captured by the lender FE and therefore omitted.

The second decomposes the shocks into contractionary β_h^+ and expansionary β_h^- components:

$$\Delta\mathcal{U}_{i,t\to t+h} = \alpha_{i,h} + \beta_h^+ \Delta\widehat{DFR}_t^+ + \beta_h^- \Delta\widehat{DFR}_t^- + \mathbf{X}_{i,t}\gamma_{\mathbf{h}} + \epsilon_{i,t+h}. \tag{7}$$

Figure 5 depicts the cumulative impulse responses of ambiguity (left column) and risk (right column) perceived by money lenders over a period of 14 days. Panel A shows the total impact β_h, Panel B the impact of contractionary shock β_h^+ and Panel C the effect of expansionary shock β_h^-.

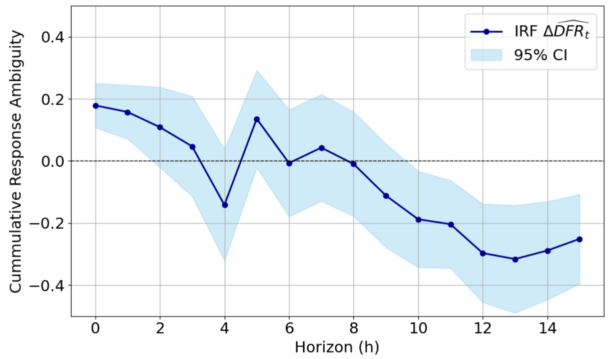
In Panels A, both ambiguity and risk respond positively to monetary policy shocks, though with different timing. Ambiguity increases immediately on the announcement date, while risk rises the following day. The effect on ambiguity is short-lived, becoming insignificant after two days and turning negative after one week—suggesting that lenders quickly incorporate the new policy information and perceive less ambiguity in the repo market. By contrast, the impact on risk is more persistent and less heterogeneous across lenders, as indicated by narrower confidence bands relative to those for ambiguity. Consistent with these findings, prior studies such as Bekaert et al. (2013), Bauer et al. (2022) and Palazzo and Yamarthy (2022) document that positive monetary policy shocks increase uncertainty, although they do not explicitly decompose it into ambiguity and risk.

Panels B and C highlight important asymmetries in contractionary and expansionary shocks respectively. Contractionary shocks raise both ambiguity and risk, accounting for most of the total effect and following the same dynamic patterns described above. Expansionary shocks, by contrast, reduce ambiguity immediately and lower risk from the day after the announcement. The magnitude of these declines is larger in absolute terms than the increases observed under tightening shocks, suggesting that easing exerts a disproportionately strong calming effect on lender perceptions. As before, the impact on risk is more uniform across lenders than the impact on ambiguity.

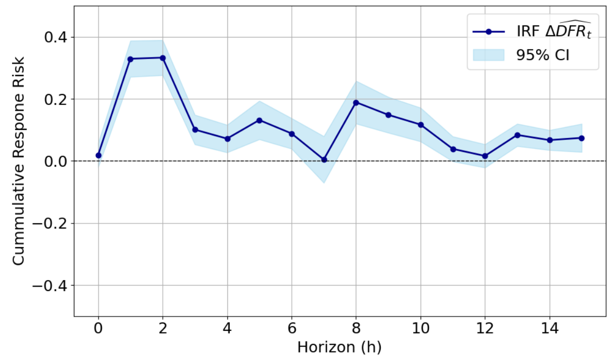
Overall, these findings show that monetary policy shocks influence perceptions of ambiguity and risk in the repo market in distinct and asymmetric ways. The brief and reversing effect on ambiguity suggests a rapid resolution of uncertainty once the policy stance is understood, while the more persistent response of risk reflects deeper, structural adjustments in how lenders price and manage known risks. Building on these insights, the next section examines how these perceptions of uncertainty influence liquidity provision in the repo markets.

Figure 5: Effects of Monetary Policy Shocks on Ambiguity and Risk

Panel A: Total Shocks ($\hat{\beta}_h$)

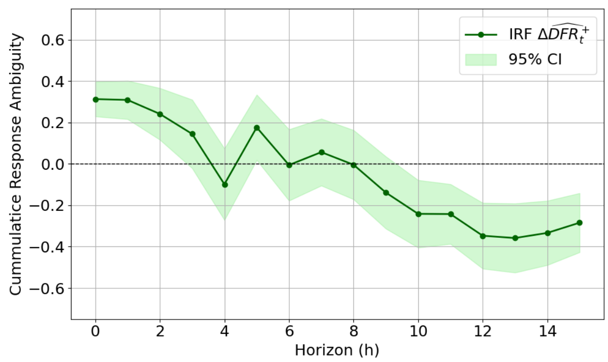


(a) Ambiguity

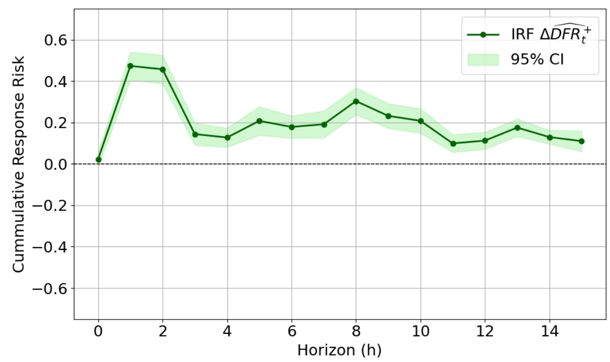


(b) Risk

Panel B: Contractionary Shocks ($\hat{\beta}_h^{+}$)

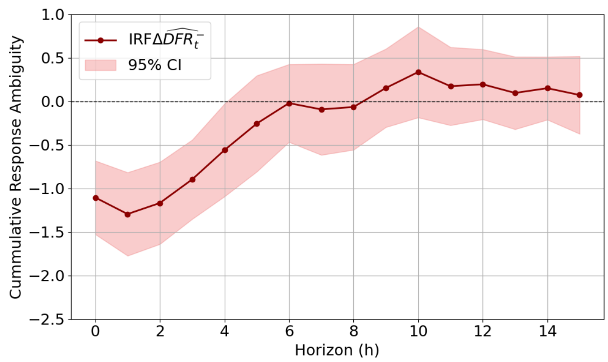


(c) Ambiguity

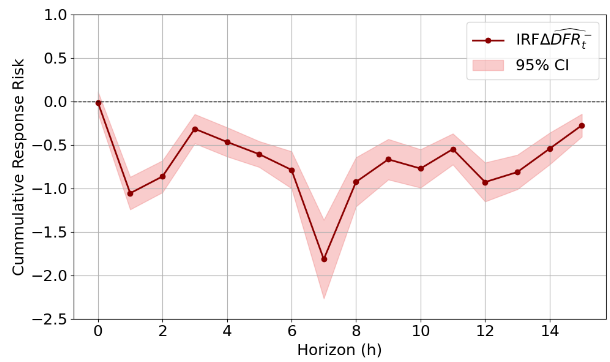


(d) Risk

Panel C: Expansionary Shocks ($\hat{\beta}_h^{-}$)



(e) Ambiguity



(f) Risk

Note: Panels A, B and C presents the coefficients β_h, β_h^{+} and β_h^{-}, obtained by estimating the regression specifications (7) and (8), respectively. The left sub-plot in each panel displays the cumulative IRF function for ambiguity, while the right plot displays the cumulative IRF of risk. The x-axis contains the impact horizon (h) measured in days, while the y-axis displays the cumulative response. The dark lines represent the coefficients, while the shaded areas around the line represent the 95% confidence interval.

5. The Ambiguity Transmission Channel

This section studies the impact of ambiguity and risk on the liquidity of the repo market. To provide a comprehensive analysis, we analyze two specific dimensions: lender level and contract level. The lender-level panel regression investigates the effects of perceived ambiguity and risk on the individual lenders' total lending volumes and their portfolio concentration across their borrowers. We measure concentration by the Herfindahl–Hirschman Index (HHI).[11] The contract-level regression studies the impact of each lender's perceived ambiguity and risk on the repo rate and lending size of each contract. In the subsequent sections, we present the main findings followed by results for sub-samples of borrowers from the Eurozone and outside of the Eurozone.

5.1. *Main Results*

Table 3 presents the results of four OLS regressions. Columns (a) and (b) are based on a lender panel comprising 52,381 observations and use logged total loan volume and the HHI as dependent variables, respectively. Columns (c) and (d) use a contract panel consisting of 22,384,665 observations and consider the repo rate and logged loan volumes as dependent variables, respectively. Each regression incorporates one-day lagged values of ambiguity and risk. In addition to these variables, our specifications include the effective level of deposit facility rate (DFR), the monetary policy shock ($\Delta\widehat{DFR}$) used in Section 4, contract terms (e.g. maturity and collateral ratings), time fixed effects (weekday, month and year), and lender or counterparty pair fixed effects. The standard error is clustered at the level of the money lender.

We first describe the regression results in the order of dependent variables and then discuss their implications.

Column (a) shows the impact of ambiguity and risk on the total loan volume of each

[11] $HHI_{i,t} = \sum_{b=1}^{B}$ share of $\text{loan}_{b,t}^{2}$ where i refers to the lender and b refers to the borrower.

Table 3: The Effect of Ambiguity, Risk on Liquidity

	Lender Panel		Contract Panel	
	Log Total Loan Volume$_{i,t}$	HHI$_{i,t}$	Repo Rate$_{s,i,b,t}$	Log Loan Volume$_{s,i,b,t}$
	(a)	(b)	(c)	(d)
$Ambiguity_{i,t-1}$	-0.69***	-0.03	0.08**	-0.13
	(0.19)	(0.04)	(0.04)	(0.25)
$Risk_{i,t-1}$	-1.22***	-0.19*	-0.76***	-2.45***
	(0.41)	(0.10)	(0.18)	(0.64)
DFR_{t-1}	-0.11***	-0.007	0.66***	0.018
	(0.04)	(0.009)	(0.02)	(0.04)
$\Delta\widehat{DFR}_{t-1}$	-0.13	-0.03	-0.25***	-0.09
	(0.16)	(0.04)	(0.03)	(0.13)
Month × Year FE	Y	Y	Y	Y
Weekday FE	Y	Y	Y	Y
Lender FE	Y	Y		
Counterparty Pair FE			Y	Y
Observations	52,381	52,381	22,384,665	22,384,665
Adj. R-squared	0.85	0.61	0.96	0.06

Note: Clustered Standard errors on the lender level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (a) and (b) display panel regressions on the lender-day level. Columns (c) and (d) display panel regressions on the transaction level.

lender. Higher levels of ambiguity and risk lead to a decrease in the total loan volume, with an increase of one standard deviation (S.D.) resulting in a reduction of 3.63% (0.69÷0.19) and 2.98% (1.22÷0.41) respectively. The average S.D. of ambiguity across lenders is 0.19, while that of risk is 0.06. Scaling the coefficients by these average S.D. values suggests that the average effect of ambiguity is larger than that of risk ($3.63\times0.19 = 0.69$ vs $2.98\times0.06 = 0.18$). In addition, a 1% increase in deposit facility rate reduces total loan volume by 0.11%, while the policy rate shock has no significant effect.

Column (b) reports the impact on portfolio concentration across borrowers. While ambiguity has no significant effect on concentration, risk significantly decreases it. A one S.D. increase leads to a 1.9% (0.19÷0.10) reduction in the average share of loans per borrower. Neither the deposit facility rate nor the monetary policy shock has a significant effect on concentration.

Column (c) shows the effects of ambiguity and risk on the repo rate at the contract level. Ambiguity increases repo rates, while risk reduces them. A one S.D. increase in ambiguity raises the repo rate by 2% (0.08÷0.04), whereas a one S.D. increase in risk lowers it by 4.2% (0.76÷0.18). Again, scaling these effects by the average S.D. values indicates that the absolute average impact of ambiguity is slightly larger than that of risk ($2\times0.19 = 0.38$ vs $4.2\times0.06 = 0.25$). In addition, a 1% increase in the deposit facility rate raises the repo rate by 0.66%, while the policy rate shock reduces it by 0.25%.

Column (d) presents the effects on the loan volume or principal value of each contract. Ambiguity has no significant impact, but risk reduces loan size. A one S.D. increase in risk lowers principal value by 3.8% (2.45÷0.64). Neither the deposit facility rate nor the monetary policy shock significantly affects loan size.

Taken together, these results indicate that ambiguity and risk reduce lending volumes in the repo market, even after controlling for the deposit facility rate and monetary policy shock. On average, the effect of ambiguity on lending volumes is larger than that of risk. Moreover while lenders reduce overall lending, higher perceived risk induces them to diversify more across borrowers, consistent with standard portfolio allocation theory under risk. At the contract level, higher risk reduce loan sizes and repo rates. By contrast, ambiguity does not affect diversification or loan size at the individual-contract level; instead, it raises repo rates, suggesting that lenders demand higher returns to compensate for heightened ambiguity.

These implications hold even when we control for monetary policy. A higher level of deposit facility rate has contractionary impacts on the repo market. Contractionary monetary policy shocks reduce the repo rate—a result that may seem counterintuitive, as it suggests an expansionary effect. However, this finding is consistent with the studies by Van Den End et al. (2020) and Cavallino and Sandri (2023), which suggest that in a low interest rate environment, such as the one observed in our data sample, the effects of contractionary (expansionary) monetary policy tend to be expansionary (contractionary).

To summarize, ambiguity significantly hinders liquidity provision in the repo market by significantly reducing the total loan volume of each lender and increasing the repo rate at the contract level. In contrast, risk has mixed effects: it reduces liquidity in terms of quantity but increases it in terms of price. Specifically, risk lowers loan volumes, yet it also reduces repo rates, thereby lowering funding costs for financial institutions. Monetary policy shocks appear to have no direct impact on loan volumes, but they do affect repo rates. However, as shown in Section 4, policy shocks have an immediate but short-lived positive effect on ambiguity and a persistent positive effect on risk. This suggests that monetary policy shocks can be partly transmitted to the repo market through changes in lenders' perceptions of ambiguity and risk. If the monetary policy shock is contractionary, ambiguity is likely to amplify its effect, whereas risk may dampen it, given their respective impacts on repo market outcomes.

5.2. Eurozone versus Non-Eurozone Borrowers

This section examines whether the previous findings hold true for borrowers both within and outside the eurozone (EZ). The exercise aims to assess whether European repo lenders' perceptions of ambiguity and risk spill over to the liquidity of borrowers outside the EZ, who account for 20.66% of all repo contracts. The model specifications are the same as those in Table 3. Table 4 presents the results, with Panel A reporting estimates for EZ borrowers and Panel B for non-EZ borrowers.

We first describe the regression results in the order of dependent variables and then discuss their implications.

Column (a) shows the impact of ambiguity and risk on the total loan volume of each lender. Ambiguity significantly reduces total loan volume only for EZ borrowers, with no effect on non-EZ borrowers. Risk significantly reduces total loan volume for EZ borrowers by 3.36% (2.22÷0.66) per one S.D. but, interestingly, increases loan volume to non-EZ borrowers by 1.93% (7.26÷3.76) per one S.D. A 1% increase in deposit facility rate reduces total loan volume of both EZ and non-EZ borrowers by 0.06% and 0.51% respectively. The policy rate shock has no significant effect on loans to EZ borrowers but increases loans to non-EZ

Table 4: The Effect of Ambiguity, Risk on Liquidity (Eurozone vs non Eurozone Borrowers)

Panel A: Eurozone Borrowers

	Lender Panel		Contract Panel	
	Log Total Loan Volume$_{i,t}$	HHI$_{i,t}$	Repo Rate$_{c,i,b,t}$	Log Loan Volume$_{s,i,b,t}$
	(a)	(b)	(c)	(d)
Ambiguity$_{i,t-1}$	-0.80*	-0.02	0.10***	0.04
	(0.43)	(0.03)	(0.03)	(0.26)
Risk$_{i,t-1}$	-2.22***	-0.18**	-0.65***	-2.44***
	(0.66)	(0.09)	(0.19)	(0.60)
DFR_{t-1}	-0.06*	-0.004	0.64***	0.03
	(0.05)	(0.01)	(0.02)	(0.04)
$\Delta\widehat{DFR}_{t-1}$	-0.32	-0.02	-0.28***	-0.09
	(0.21)	(0.04)	(0.04)	(0.14)
Month × Year FE	Y	Y	Y	Y
Weekday FE	Y	Y	Y	Y
Lender FE	Y	Y		
Counterparty Pair FE			Y	Y
Observations	52,381	52,803	17,762,556	17,762,556
Adj. R-squared	0.65	0.49	0.96	0.07

Panel B: Non-Eurozone Borrowers

	Lender Panel		Contract Panel	
	Log Total Loan Volume$_{i,t}$	HHI$_{i,t}$	Repo Rate$_{s,i,b,t}$	Log Loan Volume$_{s,i,b,t}$
	(a)	(b)	(c)	(d)
Ambiguity$_{i,t-1}$	-0.35	-0.04	0.007	-0.75***
	(1.11)	(0.04)	(0.07)	(0.23)
Risk$_{i,t-1}$	7.26*	0.27	-0.86***	-1.68**
	(3.76)	(0.20)	(0.16)	(0.68)
DFR_{t-1}	-0.51*	0.005	0.77***	0.008
	(0.30)	(0.02)	(0.02)	(0.05)
$\Delta\widehat{DFR}_{t-1}$	1.37***	0.07*	-0.09***	0.03
	(0.49)	(0.04)	(0.02)	(0.08)
Month × Year FE	Y	Y	Y	Y
Weekday FE	Y	Y	Y	Y
Lender FE	Y	Y		
Counterparty Pair FE			Y	Y
Observations	52,381	52,381	4,622,109	4,622,109
Adj. R-squared	0.80	0.55	0.93	0.10

Note: Clustered Standard errors on the lender level in paranthesis. *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$. Panel A displays the regression for repos with eurozone borrowers. Panel B displays the regressions for repos with non-eurozone borrowers. Columns (a) and (b) display panel regressions on the lender-day level. Columns (c) and (d) display panel regressions on the transaction level.

borrowers by 1.37%.

Column (b) reports the effects on portfolio concentration across borrowers within the EZ and non-EZ groups, reflecting how lenders diversify their loans among borrowers in each group. Ambiguity has no significant effect on concentration in either group. Risk affects concentration only for EZ borrowers, reducing it significantly by 0.18%. The policy rate shock has no significant effect on EZ borrower concentration but increases concentration among non-EZ borrowers by 0.07%.

Column (c) shows the effects of ambiguity and risk on the repo rate at the contract level. Ambiguity significantly increases repo rates only for EZ borrowers, while risk reduces rates for both groups, with the absolute effect slightly larger for non-EZ contracts. A 1% increase in the deposit facility rate raises the repo rate by 0.64% for EZ contracts and 0.77% for non-EZ contracts. The policy rate shock reduces the repo rate by 0.29% for EZ contracts and 0.10% for non-EZ contracts.

Column (d) presents the effects on the loan volume of each contract. Ambiguity has no significant effect for EZ borrowers but significantly reduces contract size for non-EZ borrowers. Risk reduces loan size for both groups. For non-EZ borrowers (Panel B), a one–S.D. increase in ambiguity lowers principal value by 3.26% (0.75÷0.23) compared with a 2.47% reduction from risk (1.68÷0.68), indicating that the negative impact of ambiguity is slightly larger. Neither the deposit facility rate nor the monetary policy shock significantly affects loan size.

To summarize, these results indicate that ambiguity hinders liquidity in both EZ and non-EZ borrowers, but through different channels. Ambiguity has no broad-based effect on both groups. Yet, when effects are significant, they are contractionary, increasing repo rates for EZ borrowers, reducing total lending to EZ borrowers, and lowering the principal value of contracts for non-EZ borrowers.

By contrast, the impact of risk appears to be driven through the diversification channel so its net impact on liquidity is unclear. Higher risk reduces lending to EZ borrowers but increases lending to non-EZ borrowers, consistent with lenders reallocating risk exposure across borders. At the same time, risk reduces contract size and repo rates for both groups, indicating a more cautious stance toward individual transactions despite the broader diversification of counterparties.

6. Conceptual Framework and Policy Implications

The empirical findings of Sections 4 and 5 highlight three key results on the interaction between monetary policy, ambiguity, and risk in the European repo market. First, the responses of ambiguity and risk to monetary policy are asymmetric: contractionary shocks increase both measures, whereas expansionary shocks reduce them. Second, ambiguity reacts immediately to policy changes, but dissipates within a few days, while risk remains elevated for a longer period. Third, ambiguity reduces liquidity provision by lowering lending volumes and raising repo rates, whereas risk has more nuanced effects—dampening loan volumes but lowering repo rates. Together, these findings uncover two distinct uncertainty channels in monetary transmission. The following discussion links these empirical results to conceptual framework and outlines their implications for monetary policy.

6.1. A Contract Level Conceptual Framework

Studying the impact of ambiguity and risk on financial assets, Izhakian (2020) predicts both a risk and an ambiguity premium on the price of a homogeneous asset. In our setting, securities are more complex, allowing lenders to adjust not only through the price channel but also along the quantity dimension.

To illustrate our results in Section 5, when both price and quantity are margins of adjustment, we conceptualize a simple two-equation framework. Let P_s^i and Q_s^i denote the price and quantity of a security contract s of lender i, and U^i denote the uncertainty index (either risk or ambiguity) perceived by lender i. Let the price and loan volume be jointly determined by the two equations:

$$Q_s^i = a - bU^i + cP_s^i \tag{8}$$

$$P_s^i = d + eU^i + fQ_s^i \tag{9}$$

where a and d are simplifications of the fixed effects, and b, c, e and f are assumed to be weakly positive parameters.[12] Intuitively, the model implies a direct negative effect of both uncertainty metrics on quantity and direct positive effect on price.

Inserting the equation for volume (price) into the price (volume) equation yields the following marginal effects of uncertainty decomposition:

$$\frac{dP_s^i}{dU^i} = \frac{e - fb}{1 - fc}, \qquad \frac{dQ_s^i}{dU^i} = \frac{ce - b}{1 - fc}. \tag{10}$$

Ambiguity Our regression in Table 3 shows that the total effect of ambiguity on loan volume is not statistically significant, suggesting $\frac{dQ_s^i}{dU^i} = 0$ and hence $ce - b = 0$ in the model. Consequently, the direct and indirect effects of ambiguity on loan volume exactly offset each other: while higher ambiguity tends to tighten lending standards and would thus lower volumes ($-b$), it simultaneously raises perceived risk premia and therefore prices, which in turn supports lending through the feedback channel $c > 0$. The resulting net effect on loan volumes is negligible. However, because the direct price effect of ambiguity ($e > 0$) remains, the model predicts a positive total effect on prices, $\frac{dP_s^i}{dU^i} = e > 0$. Consistent with this mechanism, regression [insert number] confirms that higher ambiguity is associated with significantly higher prices.

Risk Empirically, our contract-level regressions in Table 3 find that both the sensitivity of loan volume to risk and the sensitivity of price to risk are negative, i.e. $\frac{dQ_s^i}{dR^i} < 0$ and $\frac{dP_s^i}{dR^i} < 0$. Within our framework, this implies both $e - fb < 0$ and $ce - b < 0$, or equivalently:

$$e < \min\left(\frac{b}{c}, fb\right). \tag{11}$$

Hence, the direct positive effect of risk on price ($e > 0$) is dominated by the indirect negative channel through loan volume: higher risk reduces loan supply ($-b$), and lower volume depresses prices through $f > 0$. Although risk may exert an upward pressure on

[12] For simplicity, we further assume $1 - fc > 0$.

prices via risk premia, this is more than offset by the contraction in loan volumes and the feedback between price and volume.

Prices versus Quantities Both the effects of ambiguity and risk on loan volumes and repo rates can be understood within the same two-equation framework linking ambiguity or risk with prices and quantities. Overall, our results suggest that lenders primarily adjust to *ambiguity* through the *price channel*: increases in ambiguity translate into higher repo rates, while loan volumes remain largely unaffected. In contrast, during periods of elevated *risk*, the *quantity channel* dominates. Higher risk leads to a contraction in loan volumes, which in turn exerts downward pressure on repo rates, even though a direct (positive) price effect of risk remains present. Thus, the price channel governs lenders' response to ambiguity and offsets any potential negative quantity impact, whereas the volume channel dominates under heightened risk.

6.2. Aggregate Implications

The behavioral motivation of these channels can be understood through the lens of lenders' diversification strategies. As shown in Column (b) of Table 3, the HHI regression results suggest that lenders diversify their borrower base during periods of heightened risk, implying that the *quantity channel* dominates. In our setting, risk reflects the volatility of lending premia—uncertainty about expected outcomes—which can be mitigated through diversification. By lending to a broader set of borrowers, including those outside the euro area, lenders can smooth fluctuations in realized premia, consistent with standard portfolio theory.

Ambiguity, however, represents uncertainty about the underlying distribution of these premia—an unawareness regarding the process that generates them. Because this form of uncertainty concerns the reliability of the distribution rather than its realizations, it cannot be as easily diversified away through portfolio adjustments or shifts in lending strategy. This explains why ambiguity has no significant effect on borrower diversification (HHI). To hedge against ambiguity, lenders therefore either demand higher compensation in the form of elevated repo rates or, particularly in the case of non-euro-zone borrowers, reduce contract volumes.

This behavior aligns with multiple-prior frameworks such as the Maxmin Expected Utility model of Gilboa and Schmeidler (1989), Robust Control Theory (Hansen and Sargent, 2001), and the Smooth Ambiguity model of Klibanoff et al. (2005), all of which predict that ambiguity-averse agents evaluate strategies under pessimistic or worst-case scenarios. As a result, lenders adopt a more conservative stance, reducing lending activity or demanding higher repo rates when facing greater ambiguity.

6.3. Policy Implications

The short-lived impulse response of ambiguity, contrasted with the persistence of risk, aligns with the framework of decision-making under Knightian uncertainty (Knight, 1921), particularly as formalized in the Expected Utility with Uncertain Probabilities (EUUP) model (Izhakian, 2017). In this framework, ambiguity represents uncertainty about the probability distribution itself—captured by the cross-scenario variance in probabilities—whereas risk reflects the dispersion of outcomes within a known distribution, captured by the within-scenario variance of outcomes. Once monetary policy signals are interpreted and beliefs about the policy regime converge, uncertainty over probabilities rapidly resolves, explaining the short-lived nature of ambiguity. By contrast, the underlying volatility of outcomes, or risk, remains elevated because the policy change alters the structural environment in which agents operate.

These findings carry important implications for the design and implementation of monetary policy. First, policymakers should recognize that ambiguity and risk constitute distinct channels in the transmission mechanism. A policy shock that unexpectedly increases ambiguity can amplify contractionary effects by constraining liquidity provision via both reduced volumes and heightened prices. Conversely, risk may dampen transmission through rate concessions. This underscores the importance of transparent communication, and consistent policy signaling to reduce uncertainty about future policy paths and prevent unnecessary increases in ambiguity.

Second, our results show that lenders can manage risk through diversification but cannot mitigate ambiguity. When ambiguity rises, lenders have little choice but to decrease lending or to increase repo rate. For central banks, this distinction implies that while risk can be addressed through prudential tools—such as capital requirements, collateral frameworks, which reduce the adverse impact of tail risk, ambiguity requires credibility and clarity of policy intent. Managing ambiguity is therefore less a regulatory issue and more a challenge of effective monetary signaling. Clear communication of policy rationale and a well-anchored reaction function help market participants interpret central bank actions consistently, thereby reducing ambiguity-driven distortions in liquidity conditions.

Third, central banks would benefit from monitoring separate indicators of ambiguity and risk, as each captures a different facet of financial stability. Ambiguity-based indicators, in particular, can serve as early-warning signals of stress when market participants become uncertain about the underlying distribution of returns or premiums, even when traditional risk metrics appear stable.

7. Conclusion

This paper develops approach for quantifying ambiguity in heterogeneous asset markets with bilateral transactions. The approach builds on Jurado et al. (2015) and Izhakian (2020), integrating their methodologies to measure ambiguity directly from market behavior. We illustrate this framework using repurchase agreement transactions of major financial institutions (money lenders) in the European Union.

Our empirical analysis shows that monetary policy shocks increase both perceived ambiguity and risk among lenders. These shocks affect repo rates in directions not fully anticipated by traditional theory, but have no significant effect on lending volumes, suggesting that monetary policy may be transmitted indirectly through changes in perceived uncertainty. Higher ambiguity tightens liquidity conditions by raising repo rates and, to a lesser extent, affecting loan volumes, with spillover effects extending to non-euro-area borrowers. In contrast, higher risk reduces lending but also partially lowers repo rates, consistent with lenders' diversification strategies.

We conceptualize these findings in a two-equation framework that jointly explains contract prices and quantities and their mediating effects. Within this model, under heightened ambiguity the price channel dominates—raising repo rates with negligible impact on contract volumes—while under elevated risk the quantity channel dominates, reducing both loan volumes and repo rates.

These findings have broader implications for understanding market behavior and monetary policy, as risk can partially be diversified away but ambiguity cannot. Therefore, lenders demand higher repo rate to compensate for ambiguity. Consequently, policy communication that inadvertently amplifies ambiguity can impair market liquidity. Recognizing and mitigating such effects should therefore be an integral part of monetary policy design and signaling.

Overall, our study underscores the importance of distinguishing between risk and ambiguity in financial markets and provides a novel, transaction-level framework for measuring ambiguity. By quantifying ambiguity directly from market behavior, we offer new insights into how uncertainty shapes liquidity and the transmission of monetary policy.

References

Aastveit, K. A., Natvik, G. J., & Sola, S. (2017). Economic Uncertainty and the Influence of Monetary Policy. *Journal of International Money and Finance*, *76*, 50–67. https://doi.org/10.1016/j.jimonfin.2017.05.003

Ahn, D., Choi, S., Gale, D., & Kariv, S. (2014). Estimating Ambiguity Aversion in a Portfolio Choice Experiment. *Quantitative Economics*, *5*(2), 195–223. https://doi.org/10.3982/QE243

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., & Ragusa, G. (2019). Measuring Euro Area Monetary Policy. *Journal of Monetary Economics*, *108*, 162–179. https://doi.org/10.1016/j.jmoneco.2019.08.016

Altavilla, C., Burlon, L., Giannetti, M., & Holton, S. (2022). Is There a Zero Lower Bound? The Effects of Negative Policy Rates on Banks and Firms. *Journal of Financial Economics*, *144*(3), 885–907. https://doi.org/10.1016/j.jfineco.2021.06.032

Bauer, M. D., Lakdawala, A., & Mueller, P. (2022). Market-Based Monetary Policy Uncertainty. *The Economic Journal*, *132*(644), 1290–1308. https://doi.org/10.1093/ej/ueab086

Baumgaertner, M. (2025). Hfdshocks [original-date: 2021-01-14T11:39:50Z]. Retrieved July 15, 2025, from https://github.com/martinbaumgaertner/hfdshocks

Bekaert, G., Hoerova, M., & Lo Duca, M. (2013). Risk, Uncertainty and Monetary Policy. *Journal of Monetary Economics*, *60*(7), 771–788. https://doi.org/10.1016/j.jmoneco.2013.06.003

Borio, C., & Zhu, H. (2012). Capital Regulation, Risk-Taking and Monetary Policy: A Missing Link in the Transmission Mechanism? *Journal of Financial Stability*, *8*(4), 236–251. https://doi.org/10.1016/j.jfs.2011.12.003

Bossaerts, P., Ghirardato, P., Guarnaschelli, S., & Zame, W. R. (2010). Ambiguity in Asset Markets: Theory and Experiment. *The Review of Financial Studies*, *23*(4), 1325–1359. https://doi.org/10.1093/rfs/hhp106

Brenner, M., & Izhakian, Y. (2022). Risk and Ambiguity in Turbulent Times. *Quarterly Journal of Finance (QJF)*, *12*(01), 1–16. https://doi.org/10.1142/S2010139222400018

Cavallino, P., & Sandri, D. (2023). The Open-Economy ELB: Contractionary Monetary Easing and the Trilemma. *Journal of International Economics*, *140*, 103691. https://doi.org/10.1016/j.jinteco.2022.103691

Chen, Q., & Han, Y. (2023). Options Market Ambiguity and its Information Content. *Journal of Financial Markets*, *64*, 100790. https://doi.org/10.1016/j.finmar.2022.100790

Coiculescu, G., Izhakian, Y., & Ravid, S. A. (2023). Innovation under Ambiguity and Risk. *Journal of Financial and Quantitative Analysis*, *Forthcoming*. https://doi.org/10.2139/ssrn.3428896

Craine, R. (1979). Optimal Monetary Policy with Uncertainty. *Journal of Economic Dynamics and Control*, *1*(1), 59–83. https://doi.org/10.1016/S0165-1889(79)80005-6

D'Amico, S., & Pancost, A. (2022). Special Repo Rates and the Cross-Section of Bond Prices: The Role of the Special Collateral Risk Premium. *Review of Finance*, *26*(1), 117–162. https://doi.org/https://doi.org/10.1093/rof/rfab028

Drechsler, I., Savov, A., & Schnabl, P. (2018). A Model of Monetary Policy and Risk Premia [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12539]. *The Journal of Finance*, *73*(1), 317–373. https://doi.org/10.1111/jofi.12539

ECB. (2023a). *MMSR Reporting Instructions* (version 3.6.1). https://www.ecb.europa.eu/stats/money/mmss/shared/files/MMSR-Reporting_instructions.pdf

ECB. (2023b). Money Market Statistical Reporting. Retrieved January 29, 2024, from https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/money_market/html/index.en.html

ECB. (2025). Official interest rates. Retrieved August 12, 2025, from https://www.ecb.europa.eu/stats/policy_and_exchange_rates/key_ecb_interest_rates/html/index.en.html

Eisenschmidt, J., Ma, Y., & Zhang, A. L. (2024). Monetary Policy Transmission in Segmented Markets. *Journal of Financial Economics*, *151*, 103738. https://doi.org/10.1016/j.jfineco.2023.103738

Ellsberg, D. (1961). Risk, Ambiguity, and the Savage Axioms. *The Quarterly Journal of Economics*, *75*(4), 643–669. https://doi.org/10.2307/1884324

Etner, J., Jeleva, M., & Tallon, J.-M. (2012). Decision Theory Under Ambiguity [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-6419.2010.00641.x]. *Journal of Economic Surveys*, *26*(2), 234–270. https://doi.org/10.1111/j.1467-6419.2010.00641.x

Fu, R., Melenberg, B., & Schweizer, N. (2023). Comment on "A Theoretical Foundation of Ambiguity Measurement" [J. Econ. Theory 187 (2020) 105001]. *Journal of Economic Theory*, *207*, 105573. https://doi.org/10.1016/j.jet.2022.105573

Gilboa, I., & Schmeidler, D. (1989). Maxmin Expected Utility with Non-Unique Prior. *Journal of Mathematical Economics*, *18*(2), 141–153. https://doi.org/10.1016/0304-4068(89)90018-9

Gilchrist, S., & Zakrajšek, E. (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, *102*(4), 1692–1720. https://doi.org/10.1257/aer.102.4.1692

Greenspan, A. (2004). Risk and Uncertainty in Monetary Policy. *American Economic Review*, *94*(2), 33–40. https://doi.org/10.1257/0002828041301551

Hansen, L. P., & Sargent, T. J. (2001). Robust Control and Model Uncertainty. *American Economic Review*, *91*(2), 60–66. https://doi.org/10.1257/aer.91.2.60

Holm, M. B., Paul, P., & Tischbirek, A. (2021). The Transmission of Monetary Policy under the Microscope [Publisher: The University of Chicago Press]. *Journal of Political Economy*, *129*(10), 2861–2904. https://doi.org/10.1086/715416

Izhakian, Y. (2017). Expected Utility with Uncertain Probabilities Theory. *Journal of Mathematical Economics*, *69*, 91–103. https://doi.org/10.1016/j.jmateco.2016.12.004

Izhakian, Y. (2020). A Theoretical Foundation of Ambiguity Measurement. *Journal of Economic Theory*, *187*, 105001. https://doi.org/10.1016/j.jet.2020.105001

Izhakian, Y. (2024). A Theoretical Foundation of Ambiguity Measurement: A Reply. https://doi.org/10.2139/ssrn.4828038

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, *105*(3), 1177–1216. https://doi.org/10.1257/aer.20131193

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk [Publisher: [Wiley, Econometric Society]]. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Karahan, C. C., & Soykök, E. (2022). Term Premium Dynamics in an Emerging Market: Risk, Liquidity, and Behavioral Factors. *International Review of Financial Analysis*, *84*, 102355. https://doi.org/10.1016/j.irfa.2022.102355

Klibanoff, P., Marinacci, M., & Mukerji, S. (2005). A Smooth Model of Decision Making under Ambiguity [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-0262.2005.00640.x]. *Econometrica*, *73*(6), 1849–1892. https://doi.org/10.1111/j.1468-0262.2005.00640.x

Knight, F. H. (1921). *Risk, Uncertainty and Profit*. Hart, Schaffner, Marx. Retrieved June 2, 2020, from https://papers.ssrn.com/abstract=1496192

Miranda-Agrippino, S., & Ricco, G. (2021). The Transmission of Monetary Policy Shocks. *American Economic Journal: Macroeconomics*, *13*(3), 74–107. https://doi.org/10.1257/mac.20180124

Mueller, P., Tahbaz-Salehi, A., & Vedolin, A. (2017). Exchange Rates and Monetary Policy Uncertainty. *The Journal of Finance*, *72*(3), 1213–1252. https://doi.org/10.1111/jofi.12499

Neuenkirch, M., & Nöckel, M. (2018). The Risk-Taking Channel of Monetary Policy Transmission in the Euro Area. *Journal of Banking & Finance*, *93*, 71–91. https://doi.org/10.1016/j.jbankfin.2018.06.003

Palazzo, B., & Yamarthy, R. (2022). Credit Risk and the Transmission of Interest Rate Shocks. *Journal of Monetary Economics*, *130*, 120–136. https://doi.org/10.1016/j.jmoneco.2022.06.004

Van Den End, J. W., Konietschke, P., SamarIna, A., & Stanga, I. (2020). Macroeconomic Reversal Rate: Evidence from a Nonlinear IS-Curve. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3610866

Wieland, V. (2000). Monetary Policy, Parameter Uncertainty and Optimal Learning. *Journal of Monetary Economics*, *46*(1), 199–228. https://doi.org/10.1016/S0304-3932(00)00023-4

DeNederlandscheBank

EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl