Agreeing on Disagreement: Heterogeneity or Uncertainty?*

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Abstract

We study whether disagreement is a useful proxy for uncertainty in the foreign exchange market using monthly forecasts for the euro, British pound, and Japanese yen against the US dollar over the 2001 - 2017 period. We obtain measures of uncertainty and find that disagreement is not robustly related to uncertainty, as results depend heavily on the forecast horizon. In addition, we find that disagreement is positively associated with market liquidity and trading activity. This confirms that disagreement is not a proper proxy for uncertainty and suggests that it is more akin to heterogeneity.

Keywords: foreign exchange markets, disagreement, heterogeneity, uncertainty

JEL classification codes: G12, G15

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1 Introduction

Although uncertainty is theoretically an appealing concept, the debate regarding the empirical measurement of uncertainty is a long-standing one. Since uncertainty is essentially unobservable, one needs to rely on proxies. In the past, several authors have argued that disagreement (or dispersion) among forecasters is a natural and useful proxy for uncertainty. Miller (1977) argues that uncertainty about future price levels implies that agents disagree about their point forecasts. Zarnowitz and Lambros (1987) note that, in the case of high uncertainty, there will be disagreement, but individual forecasters will also be uncertain about their own forecasts. They demonstrate this through wide confidence bounds around the point forecasts.

The more recent empirical literature, however, casts doubt on the propriety of using disagreement as a proxy for uncertainty. For instance, Bomberger (1996) analyzes the relation between disagreement and uncertainty using inflation forecasts and concludes that the two often comove but are not the same. Giordani and Soderlind (2003) show, however, that disagreement is a better proxy of inflation uncertainty than what previous literature has indicated. Furthermore, Lahiri and Sheng (2010) argue that disagreement is only a good proxy for uncertainty when the variance of aggregate shocks is small, and Rossi et al. (2016) find that disagreement only captures a tiny fraction of uncertainty.

This article extends the analysis of whether disagreement is an appropriate proxy for uncertainty by considering a survey dataset of market participant and analyst forecasts that covers the euro, British pound and Japanese yen vis - à - vis the U.S. dollar over four forecast horizons spanning the sample period of 2001 to 2017. This represents a particularly long period, with several tranquil and turbulent episodes and, to the best of our knowledge, a different economic variable than typically studied for this question. One of the main benefits of focusing our analysis on the foreign exchange market is that our results will not be affected by short sale constraints[1]. This reason was also brought forward by Beber et al. (2010).

The foreign exchange market is an important but relatively unnoticed asset class in

[1]As Goetzmann and Massa (2005) note, differences of opinion can have a different impact on returns when there are short selling constraints which limit market participation.

regard to measurements of uncertainty and disagreement. It is important due to its sheer size, and because several authors have linked disagreement to foreign exchange puzzles and risk premia. For instance, Fisher (2006) proposes a model where the foreign exchange forward premium depends on the diversity of prior beliefs about a country's inflation process. Gourinchas and Tornell (2004) propose investors' distorted beliefs about interest rates as an explanation for both the forward premium puzzle and the delayed overshooting puzzle. Similarly, Beber et al. (2010) show that disagreement about future currency returns has a large impact on currency risk premia, and Spronk et al. (2013) demonstrate that carry traders in a heterogeneous agent model are part of the explanation of foreign exchange rate puzzles. The foreign exchange market is also relatively unnoticed, as most of the literature that evaluates measures of uncertainty and disagreement tend to focus on macroeconomic variables, such as inflation and economic output (Lahiri and Sheng, 2010; Jurado et al., 2015; Rossi et al., 2016) or company earnings and stock returns (Diether et al., 2002; Johnson, 2004). The current study thus provides an interesting complement to previous work.

Following Lahiri and Sheng (2010), Jurado et al. (2015), and Rossi et al. (2016), we define uncertainty as the variance of the unforecastable component of exchange rates, i.e., the variance of forecast error. We calculate the measures of disagreement and uncertainty based on a monthly exchange rate survey database that includes the three most actively traded currencies vis - à - vis the U.S. dollar. With these explicit measures for disagreement and uncertainty, we directly assess their relationship while controlling for market risk, which might also affect disagreement.

Whereas uncertainty is one cause for disagreement, the alternative explanation is that disagreement reflects heterogeneous probability beliefs (Varian, 1985). This heterogeneity might arise, for example, when individual forecasters use different forecasting models, or have access to asymmetric information. Under such circumstances, individual forecasters will disagree and, hence, give dispersed point forecasts. In contrast to uncertainty-driven disagreement, heterogeneity-driven disagreement does not necessarily coincide with individual forecasters being uncertain about their point forecasts.

A number of papers have studied how heterogeneity in agents expectations affects asset prices; see, for instance, Fama and French (2007), Diether et al. (2002), and Hong and Sraer (2016). Jongen et al. (2012) find that dispersion in beliefs about foreign exchange rates is driven by heterogeneous and time-varying weights on subsets of public information (such as the interest differential, past returns, and fundamental value estimates). Heterogeneity can also be based on information asymmetry; see Shalen (1993). Finally, even if agents have access to the same information and use the same models, limited attention to public information might cause forecasts to be dispersed (DellaVigna and Pollet, 2009).

To assess the extent to which disagreement captures heterogeneity, we test the impact of disagreement on foreign exchange trading activity and market liquidity. Heterogeneity has a potentially positive effect on trade by creating scope for transactions between agents with different views (Hong and Sraer, 2016; Naes and Skjeltorp, 2006). It is by now well established that the large volume of foreign exchange markets cannot be explained by international trade alone (Frankel and Froot, 1990) and that heterogeneity of market participants is necessary to explain such large volumes[2]. A positive relation between heterogeneity and volume is documented by, among others, Harris and Raviv (1993), Buraschi and Jiltsov (2006) and Banerjee and Kremer (2010). Lee and Swaminathan (2000) use high trading volume as a proxy for differences of opinion. Carlin et al. (2014) find that higher levels of disagreement in the mortgage-backed securities market are followed by higher volume and higher volatility.

Whereas heterogeneity may have a positive effect on volume, market conditions generally deteriorate when there is high uncertainty, leading to lower volumes of trade and worsened liquidity. Overall, investors become more hesitant to update their portfolios (de Castro and Chateauneuf, 2011) given that, in times of high uncertainty, valuation is more difficult and agents might not be able to consistently order portfolio preferences (Easley and O'Hara, 2010). There is also some evidence that uncertainty affects nonparticipation (Easley and O'Hara, 2009). We therefore hypothesize that uncertainty should have a negative effect on trading activity and market liquidity, whereas heterogeneity should have a positive effect on these measures.

[2]See Hong and Stein (2007) for an overview of the literature on disagreement and volume.

In this article, we provide several contributions to the literature and corroborate some of the earlier results from different markets and asset classes. We find that disagreement is an unstable proxy for uncertainty, as the results are conditional on the forecast horizon. Only for relatively short forecast horizons is disagreement related to uncertainty. These results are consistent with the findings of Bomberger (1996), Lahiri and Sheng (2010), and Rossi et al. (2016) for macroeconomic variables. Moreover, consistent with Hong and Stein (2007), we find that disagreement is positively related to both the excess number of trades and market liquidity. These results are especially strong for the longer forecast horizons and become stronger once we control for risk and uncertainty. This confirms our earlier findings that disagreement is not a stable proxy for uncertainty and suggests that it is more akin to heterogeneity.

The remainder of this article is organized as follows. In Section 2, we derive our measures of disagreement, uncertainty, and risk. We also postulate hypotheses for the relations between those variables, and their impact on foreign exchange trading volume and market liquidity. In addition, the construction of the exchange rate survey is outlined. Our empirical results are provided and discussed in Section 3. Finally, Section 4 concludes the article.

2 Methods and data

2.1 Disagreement, uncertainty, and risk

Following Jurado et al. (2015) (JLN), we assume that uncertainty about a certain economic variable, y_t, is related to the unpredictability of that variable rather than its variability and can therefore be defined as "the conditional volatility of the purely unforecastable component of the series."[3]

$$U_t^y(h) = \sqrt{E\left[\left(y_{t+h} - E\left[y_{t+h}|I_t\right]\right)^2|I_t\right]} \tag{1}$$

[3]We follow the notation of Jurado et al. (2015) here. In the notation of Lahiri and Sheng (2010), this would read as $U_t^y(h) = \sqrt{(A_t^y - F_t^y)}$ with A_t^y and F_t^y, representing the realized value and the mean forecast of the exchange rate, respectively.

In JLN, the forecastable component $E[y_{t+h}|I_t]$ is obtained by forming factors from a large set of predictor variables and using these in a diffusion index forecast. Aggregate macroeconomic uncertainty is then computed as a weighted average of the uncertainties of individual macroeconomic series. To mimic the methodology of JLN as closely as possible, we could have calculated our measure of uncertainty by generating forecast errors from a large number of forecasting models. However, as Scotti (2016) argues, survey responses are public information, and thus market participants have access to them. In addition, it is well-known that macrovariables are more predictable than exchange rates (Rossi, 2013), and thus the methodology of JLN is more suitable for such variables.

We modify the JLN methodology by taking survey forecasts rather than model-generated forecasts. Specifically, each survey respondent j has an expectation at time t, $E_j[y_{t+h}|I_{jt}]$, of the exchange rate y at horizon h, based on all information available to him/her at time t, denoted by I_{jt}. The aggregate expectation is then equal to the unweighted average over all respondents.

$$E[y_{t+h}|I_t] = (1/J)\sum_{j=1}^{J}(E_j[y_{t+h}|I_{jt}]) \tag{2}$$

Uncertainty in exchange rate y is then measured by entering Equation (2) into Equation (1). That is, similar to Scotti (2016), uncertainty is obtained by using the latest realized value of y_{t+h} normalized by the standard deviation:

$$U_t^y(h) = \frac{\sqrt{\left[(y_{t+h} - E[y_{t+h}|I_t])^2\right]}}{\sigma_t} \tag{3}$$

in which σ is the 12-month rolling standard deviation of the numerator.

Note that our proposed measure of uncertainty is quite similar to the decomposition in Lahiri and Sheng (2010) and Bomberger (1996). However, they label the common components, or the variance of aggregate shocks, as mean forecast uncertainty (i.e., the uncertainty of choosing the mean forecast), and the total of the variance of aggregate shocks *and disagreement* as aggregate uncertainty (Lahiri and Sheng) or individual uncertainty (Bomberger). Scotti (2016) also computes an uncertainty index based on forecast errors from survey participants. However, she uses the mean forecast of Bloomberg responses and aggregates the forecast errors of several macroeconomic variables.

Finally, we measure disagreement by the cross-sectional standard deviation of forecasts:

$$Dis_{th} = \sqrt{(1/J) \sum_{j=1}^{J} \left(E_j \left[y_{t+h} | I_{jt}\right] - E\left[y_{t+h} | I_t\right]\right)^2} \tag{4}$$

2.2 Data

Based on the methodology laid out above, we use a dataset with foreign exchange forecasts[4], the realized outcomes of those forecasts, and data on volatility and trading activity.

There are several reasons why foreign exchange survey data is appropriate when studying disagreement. Expectations are not directly observable, as they are an input to an investment decision. As such, we need to rely on revealed or stated beliefs when constructing a measure of disagreement. Given that financial decisions are typically the result of a combination of preferences and beliefs and are therefore difficult to disentangle, we opt for stated beliefs. One possible issue with surveys is that forecasters might not report their true expectations, i.e., their forecasts may not coincide with their stated beliefs. This issue is mitigated by the specific survey we use, as the names (companies) are revealed and the forecasters' reputation is therefore affected. In a recent paper, Gennaioli et al. (2015) illustrate the substantial information content of survey data. Survey data is similar in nature to the analyst forecasts, which many studies use to measure disagreement as it captures the forecasts of market participants about a financial variable (e.g. Anderson et al., 2005; Diether et al., 2002).

We obtain forecasts from a large survey executed among foreign exchange dealers and analysts by Reuters. The forecasters are representatives from 85 major financial institutions; the full list of names is given in Table (8) in the appendix. The survey data contains point forecasts of the exchange rate for three of the largest and most liquid currency pairs: the euro, British pound, and Japanese yen against the US dollar from 2001 to mid-2017 at the monthly frequency. On average, approximately 60 forecasters

[4] The interest in studies using survey data in financial economics has been increasing in recent years; see for example Gennaioli et al. (2015), Greenwood and Shleifer (2014), and Ben-David et al. (2013).

participate in the survey and give their forecast for one, three, six and 12 months ahead. At the start of the sample, the average number of forecasters is approximately 50; this increases to 60 in 2008; see Figure 2 in the appendix. Table 1 gives the number of forecasters per currency-horizon pair. The numbers are highly similar across currencies and horizons, suggesting that they either give all their forecasts or none. The number of forecasts ranges between 40 and 70. Given that the total number of institutions is 85, the response rate is rather high. In general, the forecasters give their forecast by the first Tuesday of the month, which is then published by Reuters the following day. We have the full list of dates available. From this data set, we compute measures of disagreement and uncertainty, as defined in the previous subsection.

Table 1: Descriptive statistics: survey

	EURUSD	GBPUSD	USDJPY	EURUSD	GBPUSD	USDJPY
		1M			3M	
Mean	55.2	53.7	54.3	58.7	57.0	57.8
Median	55.5	54.0	54.5	60.0	58.0	58.0
Min	41.0	40.0	40.0	39.0	38.0	37.0
Max	66.0	64.0	65.0	72.0	68.0	71.0
St.Dev	4.8	4.9	4.9	6.0	5.7	6.0
		6M			12M	
Mean	57.8	56.1	57.0	57.8	56.2	57.0
Median	58.0	57.0	57.0	58.0	57.0	57.0
Min	40.0	38.0	38.0	39.0	38.0	37.0
Max	71.0	68.0	70.0	71.0	68.0	70.0
St.Dev	5.7	5.4	5.7	5.8	5.7	5.8

Notes: This table presents the number of survey respondents per currency-horizon pair.

We extract realized exchange rates and implied volatilities from Thomson Reuters (obtained through Datastream)[5]. Intraday data is obtained from the Reuters Tick Capture Engine (RTCE)[6]. Because the foreign exchange market is decentralized, there is no direct measure of trading volume that captures the volume of the whole market. The RTCE data provides us with the number of trades, which is a good proxy for volume since trade size is highly standardized in the currency markets that we consider. In line with previous literature on volume, we will work with excess trading activity rather than

[5]Thomson Reuters provides FX implied volatility indices per currency based on at-the-money call and put options at constant maturity points for a set of different maturities. We match the maturity of the implied volatility with the forecast horizons as closely as possible.

[6]For most of our sample period, most interdealer FX trading is executed on either the Reuters or EBS platform. Although EBS is the main trading platform for the large currencies, a substantial amount of trading for these currency pairs takes place via RTCE. This is less the case for the Japanese yen - US Dollar currency pair, so the trade activity and liquidity measures for the yen are slightly lower and less representative of the entire market.

gross trading activity; see e.g., Llorente et al. (2002). In this way, we control for the trend in trading volume. Specifically, we obtain:

$$ExcVol_t = log(volume_t) - log\left(\frac{\sum_{s=1}^{N} volume_{t-s}}{N}\right) \tag{5}$$

in which we take N equal to the forecast horizon h.

In addition, we consider the effects of disagreement on FX market liquidity. We measure market liquidity as the bid-ask spread (relative to the mid-quote):

$$Liq_t = 100 * (S^{ask} - S^{bid})/S^{mid} \tag{6}$$

The measures for trading activity and liquidity are calculated over the exact same period as the forecasting horizon for the FX polls. We match the forecast horizon by obtaining the number of days between each poll date and forecasted date and calculate excessive trade or liquidity over that exact period. For example, if there are 24 days between today's poll and the date for which the (one-month) forecast is made, excessive trade (cumulative) and liquidity (average) are calculated over the coming 24 days.

The descriptive statistics in Table 2 show a number of interesting patterns. First, we observe that disagreement and uncertainty consistently increase as the forecast horizon increases. This suggests that forecasting becomes increasingly challenging as the horizon expands (Andrade et al., 2016). This is also reflected in the increasing range and standard deviations over the forecast horizons. Although the differences are relatively small, it is interesting to compare uncertainty across currencies[7]. We observe that the forecasters are least uncertain about the British pound. They are most uncertain about the yen. This ranking is in line with the volatilities of the currencies.

The descriptive statistics of the market-based variables in Table 3 also reveal a number of interesting patterns. First, there is a clear ranking in liquidity: the pound is the most liquid, followed by the euro and then the yen. This might reflect the characteristics of the RTCE platform, on which the commonwealth currencies are especially heavily traded. Implied volatility increases with maturity, reflecting the widely documented volatility

[7]Disagreement cannot be compared across currencies as it is not unit free.

Table 2: Descriptive statistics: survey-based variables

	EURUSD				GBPUSD				USDJPY			
	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
	DISAGREEMENT											
Mean	0.021	0.036	0.052	0.072	0.025	0.042	0.059	0.079	1.876	3.236	4.578	6.340
Median	0.020	0.034	0.048	0.066	0.024	0.039	0.055	0.075	1.810	3.210	4.471	6.209
Maximum	0.049	0.102	0.199	0.243	0.063	0.090	0.113	0.141	4.860	5.924	8.370	10.463
Minimum	0.011	0.020	0.027	0.041	0.013	0.022	0.037	0.049	0.883	1.852	2.580	3.310
Std. Dev.	0.006	0.011	0.021	0.026	0.007	0.012	0.015	0.018	0.508	0.724	1.005	1.399
Observations	210	210	210	210	210	210	210	210	210	210	210	210
	UNCERTAINTY											
Mean	0.023	0.044	0.063	0.078	0.019	0.036	0.055	0.072	0.023	0.044	0.066	0.104
Median	0.019	0.040	0.062	0.068	0.017	0.031	0.045	0.062	0.019	0.036	0.059	0.106
Maximum	0.107	0.192	0.185	0.213	0.089	0.185	0.267	0.287	0.092	0.146	0.191	0.224
Minimum	0.000	0.001	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.001	0.000	0.001
Std. Dev.	0.019	0.033	0.041	0.055	0.016	0.031	0.044	0.056	0.017	0.033	0.047	0.055
Observations	210	209	206	200	210	209	206	200	210	209	206	200

Notes: This table presents the descriptive statistics of the survey-based variables. Disagreement is given by Equation (4) and uncertainty by Equation (3).

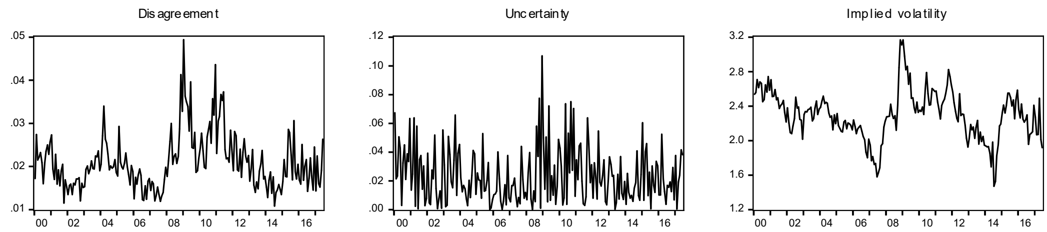
Table 3: Descriptive statistics: market variables

	EURUSD				GBPUSD				USDJPY			
	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
	BID-ASK SPREAD											
Mean	0.134	0.137	0.134	0.129	0.021	0.023	0.023	0.023	0.302	0.330	0.331	0.338
Median	0.056	0.058	0.065	0.073	0.019	0.021	0.021	0.022	0.162	0.211	0.221	0.267
Maximum	1.396	0.934	0.698	0.554	0.081	0.068	0.053	0.042	9.962	3.815	1.940	1.151
Minimum	0.016	0.020	0.027	0.032	0.009	0.012	0.013	0.015	0.026	0.034	0.047	0.057
Std. Dev.	0.210	0.174	0.150	0.115	0.010	0.008	0.007	0.006	0.776	0.546	0.388	0.291
Observations	210	209	205	197	210	209	205	197	210	209	205	197
	IMPLIED VOLATILITY											
Mean	10.341	10.452	10.570	10.708	9.143	9.303	9.475	9.649	10.400	10.395	10.504	10.673
Median	10.000	10.350	10.400	10.450	8.400	8.581	8.790	9.032	9.950	9.950	10.125	10.250
Maximum	23.750	22.150	20.000	18.600	25.300	23.000	21.700	20.100	23.000	21.000	18.800	17.250
Minimum	4.350	4.890	5.350	5.740	4.600	5.050	5.450	5.650	5.000	5.575	6.262	6.800
Std. Dev.	3.041	2.812	2.619	2.462	3.164	2.821	2.620	2.465	2.680	2.354	2.172	2.097
Observations	210	210	210	210	210	210	210	210	210	210	210	210
	EXCESS TRADE											
Mean	-1.951	-7.322	-14.418	-29.538	-1.764	-6.727	-13.491	-27.001	-2.599	-9.565	-19.668	-40.543
Median	-1.206	-7.103	-13.612	-28.978	-1.236	-6.110	-13.295	-26.692	-1.927	-8.972	-19.017	-38.275
Maximum	8.810	6.286	5.120	-2.488	8.424	1.704	-2.549	-8.951	8.468	6.706	-0.226	-14.403
Minimum	-19.278	-23.544	-35.749	-59.104	-15.329	-21.596	-28.230	-48.452	-16.131	-30.820	-48.081	-77.167
Std. Dev.	3.849	5.584	7.344	11.269	3.822	4.789	5.570	7.354	4.304	6.817	8.553	12.426
Observations	210	209	205	197	210	209	205	197	210	209	205	197

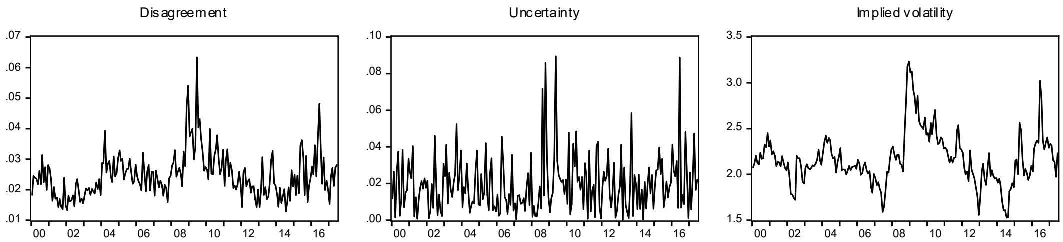
Notes: This table presents the descriptive statistics of the market-based variables. Liquidity, as measured by the bid-ask spread, is given by Equation (6). Implied volatility is the volatility implied from the currency options with maturity corresponding to the forecast horizons. Excess trade is given by Equation (5).

Figure 1: Uncertainty, risk, and disagreement

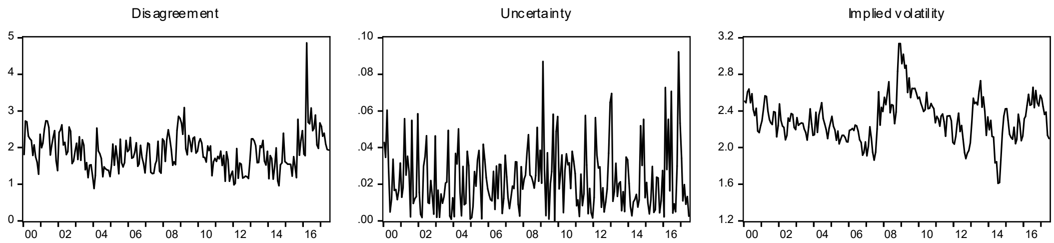
(a) EURUSD



(b) GBPUSD



(c) USDJPY



Notes: This figure presents the disagreement, uncertainty, and implied volatility for all three currency pairs. We used the 1-month forecast horizon to calculate the measures in these figures.

skew of foreign exchange options. The British pound is the least volatile currency; the euro and yen have slightly higher but comparable volatilities. The excess trade numbers are generally negative. This implies a downward sloping trend in the number of trades over our sample period for all three currencies. This finding is particularly strong for the yen.

Figure 1 provides a graphical representation of our main variables of interest, namely, disagreement, uncertainty, and implied volatility. We take the one-month forecast horizon; patterns are qualitatively similar for the other forecast horizons. First, we observe that the time-series trends are quite similar across the four variables, for all currencies. This reflects the fact that the four variables measure related concepts. The main difference between the variables appears to be in variability; uncertainty is most volatile, followed by disagreement and implied volatility. Large spikes in the variables can be matched with important economic events. For example, all variables clearly jump in the end of 2008, corresponding to the Lehman Brothers bankruptcy. The Lehman-effect appears to be somewhat less important for the Japanese yen, especially its disagreement. The euro measures subsequently show sharp increases in 2010 and 2011. This coincides with the developments related to the Greek debt crisis. After the 'Whatever it takes' speech by ECB president Draghi in July 2012, we observe that all measures drop to historical lows for the euro. Clearly recognizable for the British pound is the jump in mid-2016, coinciding with the EU referendum. The Japanese yen also shows a remarkable jump at the end of 2016. This coincides with the election of Donald Trump as president of the United States, which was perceived as an important factor for the Japanese international trade position and, thereby, its currency.

Table 4, finally, presents the correlations between our variables of interest. Within the three currencies, the correlations are quite consistent: Risk, uncertainty, and disagreement are positively correlated to each other, confirming the results from Figure 1. Risk and disagreement show an especially strong correlation of approximately 60%. All three measures are weakly negatively correlated to excess trade and strongly positively correlated to the bid-ask spread. Hence, at first sight, it appears that all three measures are negatively related to market activity using data from the 1-month forecast horizon. Excess trade and bid-ask spread, finally, are negatively correlated, which can be expected. Across currencies, we observe that the variables have a strong and positive correlation. This finding suggests that there is a positive association between the economic circumstances in the three markets.

2.3 Methodology

To evaluate the extent to which disagreement proxies uncertainty, we run two sets of tests. First, we compare disagreement with our measure of uncertainty. Second, we look into the implications that risk, uncertainty, and heterogeneity might have for market trading activity and liquidity. Specifically, for the first set of tests we use OLS to estimate the relationship between disagreement and uncertainty, controlling for risk. We include risk

Table 4: Descriptive statistics: Correlations

	EURUSD					GBPUSD					USDJPY				
	Dis	Unc	Risk	Trade	Liq	Dis	Unc	Risk	Trade	Liq	Dis	Unc	Risk	Trade	Liq
Dis	1.000	0.160	0.649	-0.050	0.229	0.630	0.120	0.597	-0.051	0.276	0.180	0.079	0.432	-0.102	-0.038
Unc		1.000	0.287	-0.053	0.313	0.075	0.470	0.217	-0.023	0.354	0.111	0.167	0.199	-0.010	0.087
Risk			1.000	-0.093	0.445	0.416	0.179	0.759	-0.026	0.483	0.258	0.094	0.609	-0.115	0.014
Trade				1.000	-0.071	-0.037	0.021	-0.032	0.783	-0.342	-0.189	-0.050	-0.065	0.559	-0.075
Liq					1.000	0.124	0.108	0.299	-0.023	0.475	0.204	0.139	0.373	-0.060	0.037
Dis						1.000	0.125	0.664	-0.054	0.254	0.301	0.062	0.469	-0.146	-0.013
Unc							1.000	0.236	0.082	0.236	0.065	0.199	0.139	0.024	0.000
Risk								1.000	-0.020	0.486	0.354	0.154	0.746	-0.129	0.050
Trade									1.000	-0.382	-0.105	-0.088	-0.053	0.573	-0.104
Liq										1.000	0.319	0.244	0.429	-0.291	0.370
Dis											1.000	0.144	0.544	-0.201	0.044
Unc												1.000	0.188	-0.031	0.111
Risk													1.000	-0.209	0.055
Trade														1.000	-0.081
Liq															1.000

Notes: This table presents the correlations between our variables of interest. "Dis" denotes disagreement; "Unc" uncertainty; "Risk" implied volatility; "Trade" excess trade; "Liq" liquidity measured as the bid-ask spread.

in the model because it can also affect disagreement by the same reasoning as uncertainty. We estimate different forms of the following empirical model:

$$Disagree_t = \alpha + \sum_{i=1}^{I} \beta^{Lag_i} Disagree_{t-i} + \beta^{Unc} Uncertainty_t + \beta^{Risk} Risk_t + \varepsilon_t \qquad (7)$$

in which *Disagree* is the cross-sectional standard deviation over the survey respondents, *Uncertainty* is the survey-based uncertainty measure given by Equations (3), and *Risk* is measured by implied volatility. For all measures, we match the forecasting horizon of the survey respondents to the horizon over which the measures are computed. We include lags of *Disagree* to account for the autocorrelation caused by the fact that the forecast horizon extends the data frequency for $h > 1$, where we set $I = 3$ for all forecasting horizons and currencies. Furthermore, we calculate robust standard errors to account for the remaining autocorrelation and heteroskedasticity.

To further assess the relation between disagreement and uncertainty, we study the effects of uncertainty on trading activity and liquidity. Market conditions generally deteriorate when there is high uncertainty, leading to lower volumes of trade and worsened liquidity. Overall, investors become more hesitant to update their portfolios (de Castro and Chateauneuf, 2011), given that, in times of high uncertainty, valuation is more difficult and agents might not be able to consistently order portfolio preferences (Easley and O'Hara, 2010). There is also some evidence that uncertainty affects nonparticipation (Easley and O'Hara, 2009). Heterogeneity, on the other hand, can have a positive effect on trade by creating scope for transactions between agents with different views (see Diether et al., 2002). A positive relation between heterogeneity and volume is documented by, among others, Harris and Raviv (1993), Buraschi and Jiltsov (2006) and Banerjee and Kremer (2010). In the model of Harris and Raviv (1993), differences of opinion arise from the heterogeneous interpretation of common information. Likewise, Lee and Swaminathan (2000) even use high trading volume as a proxy for differences of opinion.

We look into the effect of risk, uncertainty, disagreement and two measures of FX market trading activity: the number of trades and liquidity. This is estimated using

$$X_{t,t+h} = \alpha + \beta^{Dis} Disagree_t + \beta^{Unc} Uncertainty_t + \beta^{Risk} Risk_t + \varepsilon_t \tag{8}$$

in which $X_{t,t+h}$ is a measure for trading activity or liquidity in the foreign exchange market from time t to $t+h$. Note that we take $X_{t,t+h}$ over the exact forecasting horizon; in other words, the survey is taken at the *start* of the period, whereas the market variables represent trading activity and liquidity over the *remaining* days of the same period. This timing reduces the possible endogeneity concerns.

We hypothesize that β^{Unc} and β^{Risk} are negative when $X_{t,t+h}$ represents excess FX trading volume, and positive when $X_{t,t+h}$ represents the bid-ask spread. These hypotheses are inspired by Bollerslev and Melvin (1994), who finds a positive relation between uncertainty and bid-ask spreads in the foreign exchange market, and Pastor and Stambaugh (2003), who finds a correlation of -0.57 between market-wide liquidity and volatility[8]. As explained above, we further hypothesize that, if disagreement captures uncertainty, then we should find a negative β^{Dis} when $X_{t,t+h}$ represents FX trading volume, and a positive β^{Dis} when X_t represents the bid-ask spread.

3 Results

3.1 Disagreement and uncertainty

Table 5 presents the estimation results of Equation (7).

Overall, the estimation results in Table 5 reveal that disagreement is positively associated with risk and, in some cases, also with uncertainty. The relationship between disagreement and uncertainty is significant in five out of 12 univariate currency-horizon pairs. The results are particularly strong at the shorter forecast horizons for all three currency pairs. The β^{Unc} estimates are significant at the 1-month horizon for all currencies, for two out of three at the 3-month horizon, and for none at longer horizons. The same conclusion holds for the multivariate regression results. The latter implies that the relationship between disagreement and uncertainty is not affected by the inclusion of risk.

[8]Excess trading volume and the bid-ask spread are negatively correlated, as seen in Table 4.

Table 5: Disagreement, uncertainty, and risk

	EURUSD				GBPUSD				USDJPY			
	1 month forecasts											
α	0.004***	0.000	-0.0091***	-0.0084***	0.006***	0.002	-0.010***	-0.010***	0.606***	0.359***	-0.683***	-0.637***
	[3.546]	[0.054]	[-2.612]	[-2.908]	[3.979]	[0.929]	[-2.820]	[-3.075]	[5.239]	[3.095]	[-2.849]	[-3.145]
β^{Unc}		0.004***		0.003***		0.004***		0.003***		0.284***		0.241***
		[5.518]		[4.935]		[4.345]		[3.712]		[3.902]		[3.201]
β^{Risk}			0.008***	0.006***			0.011***	0.009***			0.741***	0.595***
			[3.951]	[3.216]			[5.025]	[4.426]			[6.854]	[5.697]
R^2	0.52	0.63	0.59	0.66	0.42	0.50	0.52	0.57	0.30	0.41	0.39	0.47
	3 month forecasts											
α	0.005***	0.003	-0.012***	-0.014***	0.005***	0.002	-0.013***	-0.015***	0.756***	0.562***	-0.875*	-0.922**
	[2.476]	[1.252]	[-2.692]	[-3.090]	[3.712]	[0.950]	[-2.251]	[-3.001]	[4.501]	[3.715]	[-1.892]	[-2.057]
β^{Unc}		0.001		0.001		0.003**		0.002***		0.205***		0.179***
		[1.523]		[1.459]		[2.460]		[2.952]		[2.958]		[2.546]
β^{Risk}			0.010***	0.010***			0.013***	0.012***			0.948***	0.877***
			[3.842]	[4.109]			[3.229]	[3.881]			[3.656]	[3.419]
R^2	0.69	0.70	0.72	0.72	0.68	0.71	0.72	0.75	0.51	0.55	0.57	0.59
	6 month forecasts											
α	0.008*	0.008	-0.020***	-0.023***	0.004***	0.003	-0.011	-0.012*	0.647***	0.693***	-0.828*	-0.656
	[1.723]	[1.632]	[-2.588]	[-2.838]	[2.325]	[1.530]	[-1.593]	[-1.938]	[3.062]	[3.417]	[-1.818]	[-1.482]
β^{Unc}		0.000		0.000		0.001		0.001		0.063		0.052
		[0.325]		[0.950]		[1.3980]		[1.556]		[1.581]		[1.219]
β^{Risk}			0.015***	0.015***			0.010***	0.010***			0.796***	0.741***
			[3.314]	[3.447]			[2.422]	[2.802]			[3.340]	[3.061]
R^2	0.70	0.70	0.72	0.72	0.81	0.81	0.82	0.83	0.66	0.64	0.68	0.66
	12 month forecasts											
α	0.010**	0.012**	-0.030***	-0.037***	0.006**	0.005*	-0.012	-0.014*	0.733***	0.765	-0.005	-0.015
	[2.191]	[2.155]	[-2.504]	[-2.613]	[2.287]	[1.837]	[-1.365]	[-1.682]	[3.111]	[2.654]	[-0.010]	[-0.029]
β^{Unc}		-0.001		0.000		0.001		0.001		-0.003		-0.013
		[-0.806]		[0.650]		[1.098]		[1.247]		[-0.111]		[-0.584]
β^{Risk}			0.021***	0.024***			0.012***	0.013***			0.363	0.402
			[3.843]	[4.098]			[2.397]	[2.687]			[1.435]	[1.559]
R^2	0.74	0.75	0.77	0.77	0.79	0.79	0.80	0.80	0.74	0.71	0.75	0.72

Notes: This table presents the estimation results of Equation (7). The estimated values for β^{Lag1}, β^{Lag2}, and β^{Lag3} are suppressed for reasons of space. Robust T-values in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.

Disagreement has a strong correlation with risk measured as implied volatility. In all but one case, both univariate and multivariate, we find a positive and significant estimate for β^{Risk}. The 12-month forecast horizon for the USDJPY is the exception to the rule[9].

Our results suggest that disagreement is not a robust measure of uncertainty because the relation is highly sensitive to the forecast horizon. These results are consistent with the findings of Bomberger (1996), Lahiri and Sheng (2010), and Rossi et al. (2016) for macroeconomic variables. To further understand the relation between disagreement and uncertainty, we now turn to our tests based on the implications of uncertainty on FX trading activity and market liquidity.

3.2 Implications for trading activity and market liquidity

Our results from Section 3.1 show that disagreement is not robustly associated with uncertainty. However, as summarized in Section 1, there is ample evidence in the literature that disagreement has implications for asset pricing and trading activity. We therefore turn to analyzing the effects of uncertainty on excess trading activity and liquidity. The results for excess trading activity can be found in Table 6.

The estimation results in Table 6 reveal that the relationship between disagreement and trading activity is significant in eight out of 12 cases in the univariate case. This is consistent with the findings of Hong and Stein (2007) for the equity market. For the euro and the British pound, the sign is positive, indicating that disagreement does not proxy for uncertainty but for heterogeneity. For the yen, the sign is negative, suggesting that disagreement captures uncertainty in that case. We also observe that the relation between disagreement and trading activity generally becomes stronger as the forecast horizon increases. In addition, the relation becomes stronger in the multivariate model when we control for uncertainty and risk. This is in line with what we would expect, as controlling for uncertainty should capture the uncertainty component in disagreement such that the heterogeneity component remains. It is only for the USDJPY currency cross at the six and 12-month horizons that we obtain a negative effect of disagreement.

[9]The estimated coefficients for the USDJPY are an order of magnitude larger than the other currency pairs. This is because disagreement is measured as the cross-sectional standard deviation of price forecasts, which is not unit free.

Table 6: Trading and disagreement, uncertainty, and risk

	EURUSD				GBPUSD				USDJPY			
	1 month forecasts											
α	-1.486**	-1.90***	1.305	1.774	-1.273	-1.174***	-1.431	-1.477	0.474	-2.088***	7.301***	6.688***
	[-1.879]	[-4.312]	[0.806]	[1.035]	[-1.399]	[-2.773]	[-0.861]	[-0.935]	[0.4372]	[-4.905]	[3.274]	[2.908]
β^{Dis}	-24.04			32.34	-19.92			-15.62	-1.691***			-0.743
	[-0.652]			[0.605]	[-0.560]			[-0.320]	[-2.868]			[-1.147]
β^{Unc}		-0.103		-0.062		-0.720		-0.696		-0.698		-0.234
		[-0.259]		[-0.146]		[-1.502]		[-1.313]		[-1.418]		[-0.468]
β^{Risk}			-1.445**	-1.925*			-0.153	0.309			-4.328***	-3.376***
			[-1.981]	[-1.863]			[-0.202]	[0.330]			[-4.461]	[-2.908]
R^2	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.01	0.04	0.01	0.06	0.07
	3 month forecasts											
α	-14.24***	-7.580***	-2.990	5.941	-9.222***	-6.020***	-2.751	2.835	4.400	-11.31***	43.13***	41.06
	[-5.311]	[-5.150]	[-0.381]	[0.886]	[-4.240]	[-6.250]	[-0.4609]	[0.444]	[0.758]	[-4.591]	[3.623]	[3.217]
β^{Dis}	155.9**			303.7***	48.02			173.0***	-4.937***			-1.613
	[2.190]			[3.630]	[1.017]			[2.679]	[-3.088]			[-0.728]
β^{Unc}		-0.895		-0.824		-1.133		-1.367		-0.136		1.337
		[-0.887]		[-0.802]		[-1.325]		[-1.590]		[-0.078]		[0.700]
β^{Risk}			-2.437	-10.72***			-2.020	-7.305**			-23.64***	-21.10***
			[-0.691]	[-3.132]			[-0.749]	[-1.986]			[-4.697]	[-2.979]
R^2	0.04	0.00	0.00	0.10	0.01	0.01	0.01	0.07	0.07	0.00	0.14	0.14
	6 month forecasts											
α	-36.31***	-12.02***	-39.23	-12.21	-22.99***	-12.41***	-4.679	11.49	19.60	-38.58***	81.85***	65.64**
	[-6.740]	[-2.563]	[-1.626]	[-0.564]	[-4.490]	[-6.028]	[-0.385]	[1.060]	[1.572]	[-6.985]	[2.414]	[2.152]
β^{Dis}	316.8***			338.2***	136.7*			391.4***	-10.22***			-7.805***
	[3.731]			[4.132]	[1.956]			[3.880]	[-4.093]			[-2.256]
β^{Unc}		-5.566*		-4.858*		-1.863		-1.988		10.17***		11.38***
		[-1.942]		[-1.699]		[-1.242]		[-1.579]		[3.044]		[3.591]
β^{Risk}			8.430	-7.990			-4.603	-21.24***			-46.66***	-30.71*
			[0.788]	[-0.821]			[-0.856]	[-3.536]			[-3.242]	[-1.849]
R^2	0.10	0.06	0.01	0.15	0.03	0.02	0.01	0.15	0.13	0.11	0.11	0.27
	12 month forecasts											
α	-113.6***	-29.58**	-239.8***	-160.5**	-34.56**	-39.85***	18.36	13.90	55.12	-100.4***	159.7	255.2***
	[-5.403]	[-2.127]	[-3.021]	[-2.260]	[-2.064]	[-5.719]	[0.490]	[0.374]	[1.627]	[-8.006]	[1.155]	[2.624]
β^{Dis}	839.6***			554.8***	77.73			436.2*	-18.69***			-12.10***
	[3.294]			[2.569]	[0.433]			[1.756]	[-3.625]			[-2.410]
β^{Unc}		-13.59		-7.842		7.919***		6.687**		16.82***		19.72***
		[-1.611]		[-0.988]		[2.840]		[2.266]		[4.803]		[5.611]
β^{Risk}			80.49***	34.68			-20.92	-39.01**			-94.46	-124.6***
			[2.406]	[0.995]			[-1.312]	[-1.982]			[-1.571]	[-2.958]
R^2	0.17	0.09	0.12	0.22	0.00	0.10	0.03	0.15	0.13	0.24	0.07	0.44

Notes: This table presents the estimation results of Equation (8) with the excess number of trades given by Equation (5) as dependent variable. Robust T-values in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.

The opposite result for the yen could be driven by the fact that the coverage of the yen on the RTCE platform is lower than for the other currencies. As observed in Table 3, trading in the yen decreases over our sample period. At the same time, we observe that disagreement is relatively flat for the yen, with a single peak toward the end of the sample. This combination could be driving the negative coefficient and should therefore be interpreted with caution.

For neither of the currency crosses do we find a strong relation between uncertainty and excess trading activity. For the majority of horizon-currency combinations, the sign for uncertainty is negative, as expected, but typically not significant. For the yen, β^{Unc} is positive and significant for the longer forecast horizons. This is interesting given that β^{Dis} is negative and significant for these cases. This might again be explained by the decay in trade in the yen on the RTCE platform.

The most robust result is the negative relation between excess trading activity and risk: for almost all specifications and horizon-currency combinations, especially in the multivariate cases, higher risk is associated with lower trading activity. This is in line with our hypothesis, as implied volatility is a direct measure of risk, which causes risk-averse agents to trade less.

Finally, we study how market liquidity is related to disagreement, risk, and uncertainty. The results are shown in Table 7. The results show that, for the short horizon forecasts (the one- and three-month forecasts), there is no clear relationship between disagreement and liquidity. Disagreement about the six- to 12-month horizons, however, is negatively associated with bid-ask spreads and, thus, positively associated with FX market liquidity. This confirms our earlier findings that disagreement does not represent uncertainty. Similar to the results on trading activity in Table 5, for liquidity we again find the opposite effect for the Japanese yen. Higher disagreement is related to higher bid-ask spreads, thus indicating that, in the case of the USDJPY, disagreement behaves more like an uncertainty measure although the results for the yen should be interpreted with caution, as explained above.

The contrast between the results for disagreement with those for risk and uncertainty are striking: whereas disagreement is typically positively associated with liquidity, both

Table 7: Liquidity and disagreement, uncertainty, and risk

	EURUSD				GBPUSD				USDJPY			
	1 month forecasts											
α	-0.011	0.023	-0.125*	-0.127**	0.003***	0.005***	-0.005*	-0.005*	0.049	0.062***	-0.024	-0.021
	[-0.466]	[4.719]	[-1.901]	[-2.041]	[2.435]	[15.42]	[-1.653]	[-1.849]	[1.351]	[4.114]	[-0.137]	[-0.112]
β^{Disp}	1.862			-0.111	0.094*			-0.045	0.015			-0.000
	[1.388]			[-0.164]	[1.711]			[-1.628]	[0.846]			[-0.005]
β^{Unc}		0.005		0.001		0.000		0.000		0.018		0.016
		[0.631]		[0.216]		[1.151]		[0.034]		[0.869]		[0.627]
β^{Risk}			0.067**	0.068***			0.005***	0.005***			0.044	0.037
			[2.206]	[2.647]			[3.434]	[3.788]			[0.572]	[0.382]
R^2	0.09	0.01	0.21	0.21	0.07	0.00	0.24	0.24	0.00	0.00	0.00	0.00
	3 month forecasts											
α	0.034	0.074***	-0.266	-0.307	0.012***	0.018***	-0.009	-0.012	-0.050	0.256***	-0.443	-0.331
	[0.602]	[4.715]	[-1.512]	[-1.683]	[3.078]	[11.97]	[-1.149]	[-1.584]	[-0.287]	[4.041]	[-0.498]	[-0.356]
β^{Disp}	1.752			-0.709	0.180*			-0.071	0.104			0.078
	[0.959]			[-0.798]	[1.839]			[-1.232]	[1.595]			[1.609]
β^{Unc}		0.024*		0.024		0.002		0.002		0.027		-0.003
		[1.171]		[1.390]		[1.013]		[1.396]		[0.764]		[-0.082]
β^{Risk}			0.152*	0.177**			0.013***	0.015***			0.315	0.159
			[1.951]	[2.295]			[3.512]	[4.412]			[0.789]	[0.352]
R^2	0.03	0.02	0.12	0.13	0.09	0.03	0.23	0.26	0.02	0.00	0.02	0.03
	6 month forecasts											
α	0.211***	0.106***	-0.191	-0.442	0.026***	0.039***	0.001	0.004	-0.648	0.693***	-1.449	-1.043
	[4.076]	[2.932]	[-0.800]	[-1.485]	[4.987]	[14.93]	[0.112]	[0.356]	[-1.481]	[3.714]	[-0.925]	[-0.712]
β^{Disp}	-0.185			-1.437**	-0.246***			0.097	0.275***			0.262***
	[-0.222]			[-2.199]	[2.590]			[0.902]	[2.531]			[2.961]
β^{Unc}		0.072*		0.078**		0.001		0.001		-0.092		-0.120
		[1.916]		[2.065]		[0.464]		[0.515]		[-1.070]		[-1.416]
β^{Risk}			0.170	0.266*			0.018***	0.013**			0.879	0.262
			[1.541]	[1.929]			[3.390]	[2.129]			[1.262]	[0.458]
R^2	0.00	0.09	0.04	0.15	0.09	0.00	0.13	0.14	0.15	0.01	0.06	0.16
	12 month forecasts											
α	0.653***	0.183***	0.770	-0.064	0.074***	0.072***	0.051*	0.026	-1.112*	1.103***	-2.610	-2.930
	[4.885]	[2.882]	[1.545]	[-0.117]	[6.516]	[16.57]	[1.953]	[1.126]	[-1.913]	[5.405]	[-1.094]	[-1.231]
β^{Disp}	-3.268***			-2.476*	0.096			-0.097	0.373***			0.330***
	[-2.608]			[-1.692]	[0.674]			[-0.668]	[3.553]			[3.170]
β^{Unc}		0.136***		0.134***		0.006***		0.007***		0.013		-0.001
		[2.383]		[2.397]		[2.600]		[2.829]		[0.230]		[-0.011]
β^{Risk}			-0.154	0.187			0.014	0.024*			1.631	0.891
			[-0.742]	[0.682]			[1.185]	[1.863]			[1.548]	[0.911]
R^2	0.06	0.21	0.01	0.23	0.01	0.10	0.02	0.14	0.21	0.00	0.09	0.20

Notes: This table presents the estimation results of Equation (8) with liquidity given by Equation (6) as dependent variable. T-values in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.

risk and uncertainty tend to have a negative relationship with market liquidity, consistent with Pastor and Stambaugh (2003) and Bollerslev and Melvin (1994). Uncertainty has a consistent positive effect on bid-ask spreads over the next h months for the euro and the British pound, implying that higher uncertainty is related to poorer market liquidity. The relation between risk and liquidity is somewhat less strong but is always negative. In the multivariate model, we observe that uncertainty tends to dominate risk.

4 Conclusion

This article has examined whether disagreement is a proxy for uncertainty in the foreign exchange market using survey data for a set of bilateral exchange rates relative to the U.S. dollar over the 2001-2017 period. Specifically, we measure uncertainty in the style of Jurado et al. (2015) and Scotti (2016) based on forecast error variance, along with implied volatility as a proxy for risk, to explain the variation in disagreement. We find that disagreement is a poor proxy for uncertainty, as our results are sensitive to the forecast horizon.

We further investigated in what way risk, uncertainty, and disagreement impact foreign exchange trading activity and market liquidity. We find that disagreement is associated with both higher market liquidity and higher trading activity, especially for the longer forecast horizons. This confirms our earlier findings that disagreement is different from uncertainty and suggests that disagreement is more akin to heterogeneity.

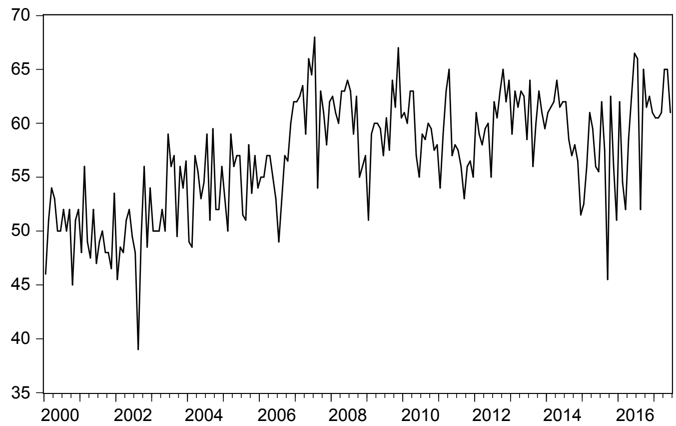
Based on these results, we can conclude that disagreement is not a robust measure of uncertainty, but does have a tendency to be a measure of heterogeneity. Our results have broad implications for several actors. First, academics should be cautious for relying too much on disagreement as a measure for uncertainty, as this is not always the case and may have possibly opposite implications for markets and market participants. Second, uncertainty-averse agents do not necessarily have to shy away from periods of high disagreement, ceteris paribus, as it may also indicate quite advantageous market circumstances. Finally, policy makers attempting to gauge the state of the market should take disagreement as a positive indicator, rather than a negative indicator, of market quality.

Appendix

Table 8: List of Forecasters

4CAST	DNB	N Bk Canada
ABN AMRO	DZ Bank	NAB
AIB	Eurobank	Natixis
ALLIED IRISH	Goldman Sach	Natl Bk Cana
Alpha Bank	Handelsbanke	NatWest Mkts
ANZ Bank	Helaba	NBG
Aurel BGC	HSBC	Nomura
Banco BPI	IDEAglobal	NORD/LB
Banco Santander	IFR Markets	Nordea Bank
Barclays	IFR-Buzz	OCBC
BayernLB	IHS GLOBAL	PNC FINL SVC
BBVA	Informa Global	Pohjola
BMO	ING	Rabobank
BNP Paribas	Intesa SP	RAIFF BNK AU
BofAML	Investec	RBC
BTMU	JP Morgan	Santander
CA CIB	Julius Baer	Saxo Bank
CBA	Jyske Bank	Scotiabank
CIBC	KBC Securities	SEB
Citi	Landsbankinn	Soc Gen
Commerzbank	LBBW	St George Ba
Continuum	LBK	StanChart
Credit Suisse	Lloyds Bank	Swedbank
Danske Bank	Macquarie Gr	TD
DBS Bk	Mizuho	TD
DekaBank	Monex Europe	UniCredit
Desjardins	Morgan Stanley	Wells Fargo
Deutsche Bank	MUFG	Westpac
		ZKB

Figure 2: Number of forecasters



Notes: This figure presents the average number of forecasters over time.

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