Forecasting Migration Movements using Prediction Markets

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Abstract

Migration forecasts are crucial for proactive immigration and integration management. While the demand for accurate migration forecasts is increasing, the current state of migration forecasting is still unsatisfactory. We introduce an alternative method to forecast potential migration movement scenarios: prediction markets. While prediction markets are mainly unknown in migration studies, they are established as highly accurate in the political economy for forecasting election outcomes. For its application to a complex phenomenon in a more constrained information environment such as migration movements, we argue that prediction markets allow to balance complementarities of current qualitative and quantitative approaches if they provide solutions to avoid thin trading and integrate expert knowledge into the market. We apply the prediction market to forecast immigration in four West European countries in 2020 and find encouraging results. We discuss the strengths and limitations of prediction markets to migration forecasting, including ethical considerations, and guide its future application.

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Introduction

The high numbers in migration movements around the year 2015 were an unexpected challenge for European destination countries. Governments, non-governmental organizations (NGOs), but also the broader society were not sufficiently prepared. Among other reasons, this was the case because none of the forecasting[1] models had predicted this increase in immigration at that time (Sohst et al. 2020). This lack of preparation had severe implications for the labor and housing market, public transport, economic growth, retirement provisions, health care, and public schools, to name but a few examples. Indeed, the rapid increase in migration in 2015 is a particular case. However, recalling migration history, quickly accelerating and strong migration movements repeatedly recur following extraordinary important political and economic events that until now were not reflected sufficiently in forecasts.

To avoid or at least minimize this reactive way of migration management and prepare for migration movements, it is vital to forecast migration dynamics as accurately as possible (Anderson 2017; Castles 2004) However, although the need is clear and the demand exists (Bijak et al. 2017; Kjærum 2020), the current state of the art on migration forecasting attempts is still unsatisfactory (Disney et al. 2015; Sardoschau 2020; Sohst et al. 2020). The main reasons are the challenges that come with forecasting (Bijak 2010), which are further amplified in a setting of high complexity and information constraints, such as the case with migration movements (Bijak & Czaika 2020; Willekens 1993).

With this Methods Note, we aim to contribute by introducing a method not yet applied in migration research and might allow for highly accurate and rapidly updated forecasts: prediction markets. Prediction markets, also known as 'information markets' or 'betting markets,' are virtual markets that work like financial markets. In contrast to financial markets, the market participants do not trade financial assets but expectations on all kinds of future events. As a group of Nobel Prize winners and other distinguished scholars in economics argue, prediction markets are better able to predict a large variety of events than traditional prediction instruments (Arrow et al. 2008). Prediction markets have been shown to be accurate in forecasting elections outcomes and foresee highly complex events such as the success of replication studies in social and behavioral science (Gordon et al. 2021). Nonetheless, prediction markets have not been used yet to predict migration movements.

In this Methods Note, we discuss the specifics of an appropriate prediction market design for forecasting complex questions in a context of a restricted information environment on an ethically challenging topic. We argue for a probability market applied to a sample consisting of a substantial number of laymen and a selected panel of experts. We apply our market design to the forecasting of immigration and asylum applications in four European countries. The results show that the prediction market can improve the forecasting of migration flows considerably.

Forecasting Migration Movements: The State of the Art

Qualitative methodological approaches for forecasting migration movements generally rely on insights from a limited group of participants, generally experts. The main strength of these approaches is that they are not necessarily dependent on migration statistics and certain model assumptions. The most prominent approach is the so-called 'migration scenario creation process,' which builds various general migration forecasts based on expert discussions and a theoretically deduced identification of migration drivers (De Haas et al. 2010; Vezzoli et al. 2017). Besides the difficulty to theoretically identify key drivers based on a complex and fragmented spectrum of migration theories (Bijak & Czaika 2020), a limitation is that the forecasts may vary strongly depending on the experts that are sampled and/or might be biased through the impact of opinion leaders.

Quantitative methodological approaches avoid the strong dependence on expert opinions through the systematic analysis of large numbers of data points and further reduce subjectivity using official migration statistics. Yet, subjectivity is inevitable, as the researcher makes model assumptions. Structural Equation Models (SEM) rely especially heavily on theoretical assumptions, and SEM international migration predictions come accordingly with high uncertainties (Burzyński et al. 2019; Dao et al. 2018). Gravity models are less theory-dependent than SEMs but must rely on almost time-invariant variables to make good migration forecasts, making them relatively rigid (Cohen et al. 2008; Hanson & McIntosh 2016). Bayesian statistical modeling became the preferred technique because it allows to include the introduced uncertainties introduced through theoretical assumptions into the model and – as shown for forecasts on asylum migration – only depends on some data distribution assumptions (Azose & Raftery 2019). The most recently developed models use machine learning models applied to the forecasting of asylum migration(Carammia et al. 2020; Robinson & Dilkina 2017).

Beyond firm reliance on theoretical assumptions, quantitative forecasting models typically suffer from limited availability and relatively poor quality of migration data. This, in turn, leads to high uncertainties in the forecasts (Abel et al. 2013; Raymer et al. 2013). The limited quality and availability of data are mainly challenging for the popular Bayesian and machine learning approaches since their usefulness depends heavily on the availability of large volumes of data that cover long time series. Data limitations also prevent forecasting migration movements for different migration categories (Sohst et al. 2020). Newer approaches compensate for poor data quality from official statistical records by using less traditional sources such as Facebook (Palotti et al. 2020; Spyratos et al. 2018) or Google search activities (Böhme et al. 2020; Wanner 2020) to forecast migration patterns. However, the improvements in the data collections come with new shortcomings regarding lacking representativity, not at least due to low internet coverage in key origin countries of interest (Carammia et al. 2020).

Probably the most promising models to accurately forecast migration movements are based on mixed-method approaches. The different kinds of uncertainties resulting from qualitative and quantitative approaches and their respective model strengths greatly complement each other. For example, Acostamadiedo et al. (2020) use qualitative migration scenarios for the guidance of the quantitative expert questionnaire, while Billari et al. (2014) proceed vice versa by using a quantitative model on top of expert projections. Although both chronological procedures may outperform prior models, they are still limited in their forecasting accuracy.

Comparisons of current attempts in migration forecasting with regards to their accuracy are difficult and consequently rare (Casagran et al. Forthcoming; Sardoschau 2020). Moreover, due to funding constraints, forecasts are often not continued over time but only for specific time points.

Continuously updating modeling systems as recommended by Bijak et al. (2017) would be necessary for allowing comparisons and forecast short-term trends like the so-called migration crisis in 2015.

To summarize, both quantitative and qualitative models of migration forecasting suffer from severe methodological or practical limitations. Consequently, mixed-method approaches aiming at exploiting the complementarities of qualitative and quantitative techniques are most promising. In what follows, we will argue for prediction markets with features of an expert panel as one such method. By letting a considerable number of laymen and a smaller sample of experts reveal their expectations on a prediction market, we will limit the dependency on the expert judgment through the wisdom of crowds without entirely erasing expert knowledge as a source of the forecasts. Furthermore, the prediction market method will avoid modeling assumptions based on the complex and manifold migration theories. Finally, in the prediction market, a continuous updating based on new information is possible, and hence the method is sensitive to short-term trends.

A Prediction Market on Migration Movements

Prediction markets, as defined by Berg et al. (2008), are Internet-based financial markets designed to use the information contained in market prices to make predictions about certain future events. The participants buy and sell (henceforth 'trade') their expectations regarding specific events, called 'contracts,' that will occur in the future. The purpose of prediction markets is to bring to light the best collective assumptions of the participants about the outcome of future events, such as migration movements. In prediction markets, the values of traded contracts depend directly on future results, and therefore the prices of these contracts provide information about the results. A prediction market looks similar to the stock market. Participants in a prediction market have selected themselves into the market and have a direct economic motivation to obtain relevant information about the event, which they try to forecast. In the case of elections, for example, they must separate political news relevant to the election from those that are not. If they have clear insights or react to new public information faster than other traders, they can make money in the market.

The theoretical backbone of prediction markets (as for any market) is the efficient market hypothesis (EMH), which states that prices reflect all information (Fama 1970; Hayek 1945). While the hypothesis might be too strong because markets might not be fully informationally efficient (Grossman & Stiglitz 1980) or there might even be 'misvaluation' as a consequence of limited rationality (Hirshleifer 2001; Kahneman & Tversky 1973), the fact that the hypothesis is debated shows how strong the price mechanism is in aggregating even highly decentralized information. A specific advantage of prediction markets relative to other markets is that since the market's time horizon is rather short, even in the case of inefficient markets, the probability of 'speculation bubbles' is small.

Prediction markets are not only based on strong theory, but they have also proven themselves in practice. Prediction markets showed to be reliable in the prediction of elections in the USA (Berg et al. 2003, 2008) and have been widely used in Europe, where they have outperformed other forecasting models based on polls, expert panels, and economic indicators (Graefe 2017). Prediction markets, however, have successfully been used for relatively simple phenomena for which data is abundant, as is the case for elections and highly complex events with limited and hard-to-access information. Indeed, prediction markets have been successfully applied to predict the success of replication studies in social and behavioral science (Gordon et al. 2021).

While prediction markets generally allow for accurate forecasts, forecasting accuracy is not constant but can vary in important ways even for the same events (Graefe 2017; Strijbis & Arnesen 2019). A much-discussed problem of prediction markets is 'thin trading' (Pennock & Sami 2007), i.e., the situation where supply and demand do not match. As a result, no market price is generated, and therefore, no forecast can be derived. The problem can occur especially in double auctions when the number of participants in a prediction market is small. To facilitate trading in the prediction market and hence avoid thin trading, automated price makers have been developed (Hanson 2003, 2007; Othman et al. 2013). An automated price maker is an algorithm that automatically offers a new price for the contract after a transaction has been executed. In this way, the organizer ensures a price offer for each trader that she can accept at any time. The obvious advantage is that the liquidity in the market is infinite. A disadvantage is that the organizer has to participate in the pricing and thus exposes herself to financial risks if the real money is used in the market. Also, while market scoring rules largely resolve issues of thin trading, they can introduce bias. In our application, we use the Logarithmic Market Scoring Rule (LMSR) developed by **hansen2007sophisticated**; Hanson (2003). The LMSR showed to be the market maker that introduces the least systemic bias into the forecasts (Dudík et al. 2017)[2].

The 'wisdom of crowds' literature, which can be traced back to Galton's 'Vox Populi' (Galton 1907), indicates that larger samples reduce prediction errors (Surowiecki 2005). Dudík et al. (2017) also demonstrate formally for prediction markets with market scoring rules that the discrepancy between market clearing prices and ground truth goes to zero as the population of traders increases. However, how much the wisdom of crowds mechanism plays in prediction markets and how many participants need to participate in a prediction market to arrive at accurate forecasts is still an unresolved issue. While the wisdom of the crowd theory suggests that the number of participants should be considerable, some argue that market efficiency is achieved already with a handful of participants. For instance, Christiansen (2007) reported that prediction markets with more than 16 participants were well-calibrated, and McHugh & Jackson (2012) found that varying the number of market traders has a minimal impact on the accuracy for markets with more than 20 participants.

Most likely, whether prediction markets are efficient with few participants depends heavily on whether the participants have access to all relevant information. Rather than via a large number of participants, relevant information can be aggregated by seeking out those individuals who have access to it. Therefore, especially when the relevant information is not readily available or hard to process for laymen, expert panels are often the choice. Consequently, and similarly, as previous studies that forecasted the success of replication studies (see above), we propose actively recruiting experts as participants in the prediction market. The information these experts bring into the market should be seen as complementary to the wisdom of crowds generated through the participation of many laymen. It is an open question—and likely dependent on the specific event that is to be forecasted—the trade-off between investing into the recruitment of (a large number of) laymen relative to (a small number of) experts is.

If the prediction market aims to forecast the likelihood of an event, a probability market needs to be applied. In probability markets, the final values of the contracts are defined as 100 if the event materializes and 0 else. Assuming risk neutral utility maximizers, this translates into probabilities. The reason is that these economically rational participants trade shares based on the probabilities they attach to events. For example, suppose a rational trader on the market thinks that the likelihood of an outcome is 60% while the share's current price is at 50. In that case, she buys as many shares until the price is at 60 because, until this value, the expected value (EV) is above 0[3].

While the probability market is the proper setup to forecast the likelihood according to which events occur, for some questions, we are not only interested in the likelihood of an event. Instead, we are also interested in the specific point estimate. For example, we might want to have a point estimate for the number of immigrants that will arrive in a given year. One option to arrive at such point estimates is defining the final value according to the specific value (e.g., 0.5 if the outcome is 500,000). This type of market, sometimes called 'vote share market', can directly generate point estimates (such as forecasts of the vote share of a given party). It has the disadvantage that it does not come with information on the uncertainty of the forecast and is particularly prone to bias introduced by market scoring rules (Arnesen & Strijbis 2015; Strijbis & Kotnarowski 2015).

In order to arrive at point estimates with uncertainty levels, we apply the so-called 'sequencing method' (Strijbis 2020). This method provides tradable contracts for different mutually exclusive ranges (e.g., ranges of the number of immigrants) and interpolates the probabilities attached to each. The interpolated outcome (e.g., number of immigrants) that lies at the 50% probability level is the point estimate since the probability of the vote being lower or higher is smaller in both cases. In addition, the resulting probability distribution can be used to arrive at probability intervals that measure the uncertainty according to which the outcome will fall into a specific range. The only major disadvantage of this approach is that the number of ranges offered as contracts for trading has to be somewhat limited to avoid market inefficiency. Hence, it must be assumed that the probability function created by interpolation approximates the true probability function that underlies the trading transactions of the participants on the market.

Forecasting Migration Movements in 2020

In the following, we apply the described prediction market to the forecasting of migration movements in 2020. The overall application setup was as follows: In May 2020, we opened the prediction market and invited the target sample of potential participants[4]. Reminders to update their 'portfolios' according to their expectations were sent to the participants in July and November 2020. The prediction market was closed with the end of the year and hence the date for which the forecast was made. In June 2021, the official statistics became publicly available for all markets, which allowed to settle the markets and calculate the final score for each participant.

Prediction markets generate forecasts for specific events. As long as the time horizon is limited, these events can be of almost any kind. However, events must be clearly defined, and hence it is vital that at a later stage, hard data exists that allows judging whether a specific event has taken place. This is the case for events for which statistical offices provide data. The number of events that can be used is also not limited as such. However, a prediction market with too many markets can lead to thin trading since the participants might concentrate on only a few.

We limited the prediction market to migration movements to four destination countries and three topics in 2020. The destination countries comprise Germany, Spain, Switzerland, and the UK. The first two being continuing EU countries, Germany known as a classic immigration country, and Spain a (still) newer immigration country. Switzerland represents a non-EU, but Schengen case and the UK a country in transition from EU to a non-EU country outside the Schengen area. The topics of the markets are for each country the number of immigrations in 2020, the number of asylum applications in 2020, and the most frequent country of origin among asylum applicants in 2020. We excluded immigration to the UK because we were unsure if the migration statistics to settle the market would be published within a reasonable time horizon and could rely only on few British participants.

The participants

In order to combine the logic of the wisdom of crowds and benefit from the experts' knowledge, we create a panel consisting of both experts and laymen. Consequently, in addition, to rely on a pool of participants that participated in prior prediction markets on elections, we actively recruited experts to participate in our market[5]. According to the logic of a decentralized aggregation mechanism of markets, these experts ideally have diverse information. To guarantee diversity, we invited migration researchers, experts from NGOs, and governmental organizations to participate.

We sampled 425 experts and invited around 550 participants of previous prediction markets on elections in Spain and Switzerland[6]. 164 individuals registered on the market, of which 97 conducted at least one trade. Of these 97 individuals, 14 were experts, 35 were former participants on prediction markets for Switzerland, and 48 on prediction markets on Spanish politics. The laymen outperformed the experts: While the laymen increased their points during the game on average from 10'000 to 13'821, the experts ended up with a mean of 11'080. This suggests that laymen in a prediction market can improve the prediction market's forecast even for such a complex question as migration flows. One reason is that highly committed laymen might have the time and motivation to seek information to arrive at well-educated guesses. However, while most of the laymen were somewhat experienced players on prediction markets, for most of the experts, this was a new experience. This suggests that if it were possible to establish a panel of expert participants willing to participate in the market for an extended period, the forecasts of the prediction market could be considerably improved. This is because the experts could improve their ability to fully take advantage of their knowledge to maximize their gains and add more information to the market.

The number of actively trading participants on our market allowed us to create market efficiency and create informed forecasts. However, the number of participants in our method application was too small to exploit a crucial potential asset of the prediction market, which is the generation of time series of quickly updated forecasts.

Ethical Considerations

Since migration and especially asylum migration is a sensitive topic, it is necessary to reflect upon the ethical dimension of each step of a new methodological approach applied to the topic. Before design and implementation, we reflected upon the intentions behind the study and its potential impact on society. This helped to set activities into relation and a proceeding of the research project in the first place. Here, the intentions are to improve current forecasting about migration movements and asylum applications to switch from reactive to proactive migration management to ease the arrival of migrants.

The aim of improving the arrival of the migrants and the participants recruited for the prediction market – migration experts and trained laymen – implies that the primary beneficiaries do not match the sample and hence the investing group. A mismatch like this is a relevant point considering the invasiveness of the study. For the expert sample, we do not expect significant invasiveness of the study and the participation. However, the trained laymen could be influenced negatively in the sense that applying the stock market view of the prediction market to the movement of actual people might change their perception of migrants and make them 'less real.' To minimize the potential for such an outcome, we briefed all participants in advance and debriefed them in the aftermath of the study.

A dilemma in designing the study was the decision regarding the incentivization of the study participants. On the one hand, research regarding prediction markets encourages a monetary incentive due to its monetary logic allowing the markets to work correctly (Luckner & Weinhardt 2007; Rosenbloom & Notz 2006; Servan-Schreiber et al. 2004). On the other hand, the financial incentives might also motivate participants to influence the study subject – migration movements – in the real world. For the trained laymen sample influencing actual migration seems to be an impossible task and is not risky. In contrast, the experts could influence migration movements since they are, by definition, people sampled from institutions that have to different degrees an impact on either immigration or integration practices. To avoid losing the monetary logic of the market while preventing a push to influence real-life migration for own monetary gains, we decided to donate the 'gains' from the market to a humanitarian organization of the participant's choice. We informed them accordingly in advance of the study.

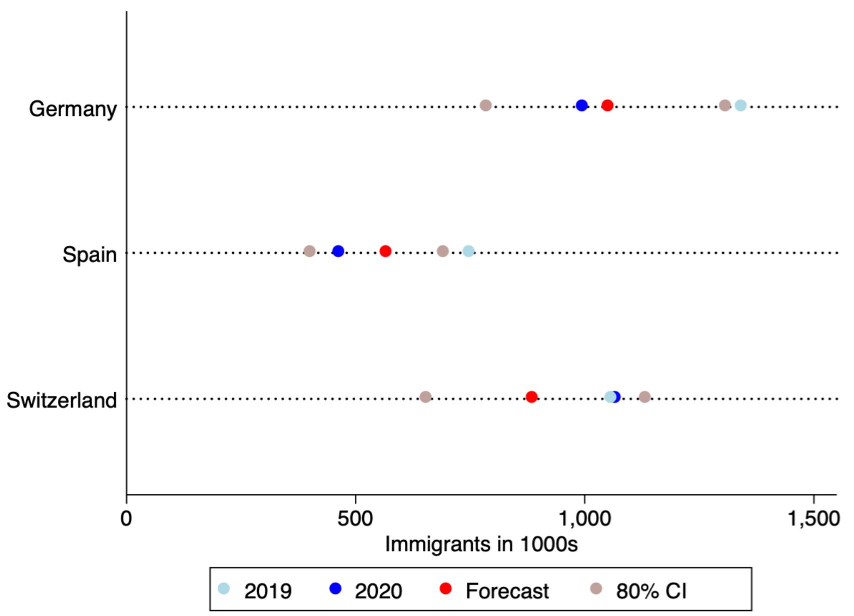
Results

In what follows, we report the accuracy of the prediction market forecasts. In order to assess the quality of the forecasts, we compare the average forecast in June for the whole of 2020 not only with the actual numbers that were made available by the statistical offices ex-post but also with those of 2019. We compare our forecasts with the numbers of 2019 not only because we are not aware of similar forecasts for this year but also because forecasts based on extrapolation are typically very dependent on the values for the previous time points and would likely have produced forecasts that were close to the actual value for 2019. Hence, we can think of prediction market forecasts that are further away from the actual value than the value for 2019 as inaccurate, those that are close as about equal, and those that are close to the outcome and far from the 2019 value as relatively accurate. Additionally, we can assess whether the actual outcome falls within the 80% interval of our forecast for the forecasts of the number of foreign immigrants and asylum seekers. We make use of the narrow 80% confidence interval that is sometimes used by election forecasting since due to considerable uncertainty of ex-ante (relative to ex-post) predictions, this confidence interval is more informative than the larger 90 to 95% intervals[7].

The first forecast to evaluate is the number of foreign immigrants in 2020. For all three countries for which we generated a forecast, the outcome was within the 80% confidence interval. The forecasts came close to the actual outcomes in Germany and Spain and more than a forecast based on 2019. In the case of Switzerland, the forecast was about as far off as the 2019 value and hence cannot be considered an improvement over forecasts based on extrapolation.

With regards to the number of asylum seekers, we can make our evaluation for all four countries. Figure 2 shows that again the real numbers were within the confidence interval. More interesting, the forecasts were closer to the outcome than the 2019 values in all four countries. While the difference between the 2019 values and the forecasts was substantial for Spain and Switzerland and can

Figure 1: Forecasting accuracy for immigration

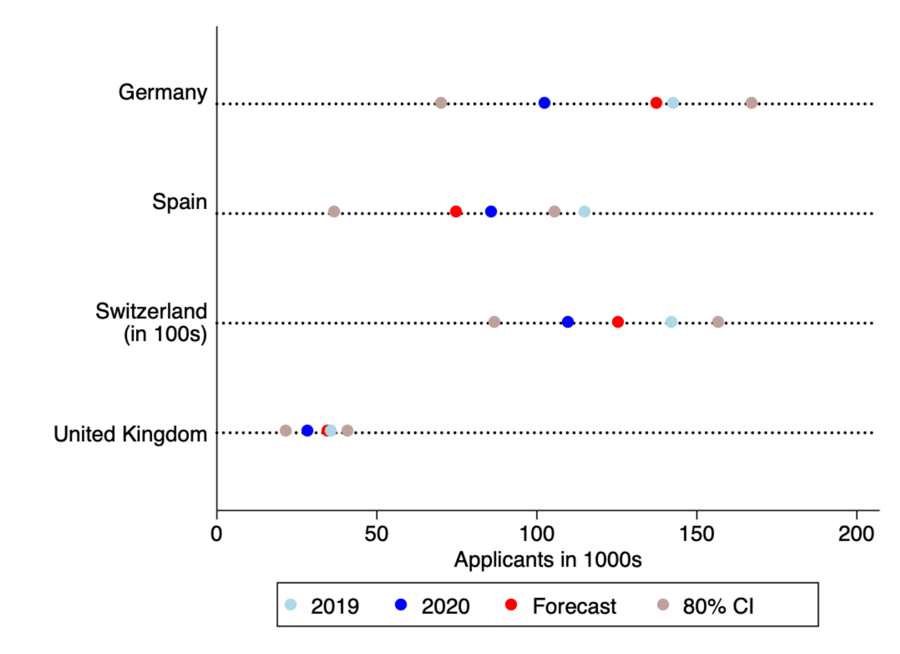


be considered an important improvement over a forecast based on extrapolation, the differences are rather negligible for Germany and the UK.

Finally, we evaluate the forecasting accuracy for the country of origin with most asylum applicants in 2020. This evaluation is more complicated than the previous ones since our forecasts consist of likelihoods with no one-to-one correspondent. Hence, to assess the forecasting accuracy, we compare whether the rank order of the probabilities correlates with the rank order of the number of asylum applications. We are particularly interested in whether the market could correctly forecast which country of origin would be the most frequent since this was the question on which the prediction market participants made the bets.

Figure 3 shows that in all four countries, the highest probability was attached to those countries of origin that turned out to be the most frequent sending states. Hence, strictly speaking, for all four countries, the forecast was correct. We can also see that in the two cases where these numbers turned out to be relatively close, the second most frequent country of origin received the second highest probability. Hence, also in these more complicated cases, the forecasts were correct. How-

Figure 2: Forecasting accuracy for asylum applications

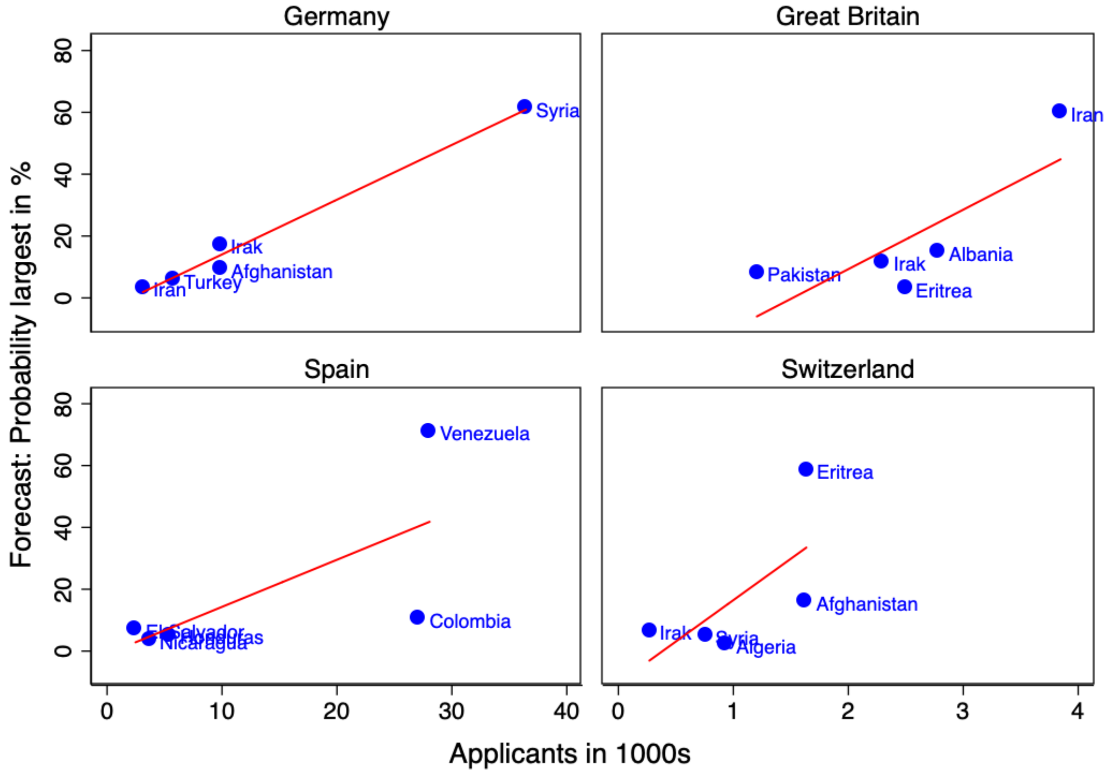


ever, one might want to argue that the probabilities of these second most frequent countries of origins (Colombia in Spain respective Afghanistan in the UK) that were clearly below 50% are underestimations of the actual probabilities at the time. While it is impossible to know whether this is true and the probabilities of the forecasts were correct, it is reassuring that with regards to the actual numbers, the forecasts about which state would be the most frequent country of origin were correct.

Conclusion

In this Methods Note, we have argued for a new method for forecasting migration movements: prediction markets. While prediction markets are mainly unknown in migration studies, they are widely applied in the political economy for forecasting election outcomes with high accuracy. For its application to a complex phenomenon in a more constrained information environment, such as migration movements, we argued that prediction markets must combine the wisdom of crowds with expert knowledge. We have also argued for a probability market and the deduction of point estimates with measures for uncertainty through sequencing.

Figure 3: Forecasting accuracy for the origin of asylum applicants



In order to assess the ability of prediction markets in general and the specific market design of this study, we applied the prediction market to forecasting immigration and asylum applications in four West European countries for 2020. As our analysis has revealed, the prediction market arrived at forecasts that were more accurate than predictions that would have been based on extrapolation. Hence, prediction markets can be considered as a highly promising method for forecasting migration flows. Yet, our application has not remained without limitations. In particular, future prediction markets should try to increase the number of experts that participate and create a larger panel of continuously active participants. This would not only increase the forecasting accuracy of the market but also allow it to fully exploit its advantages by generating an extended time series of updated forecasts.

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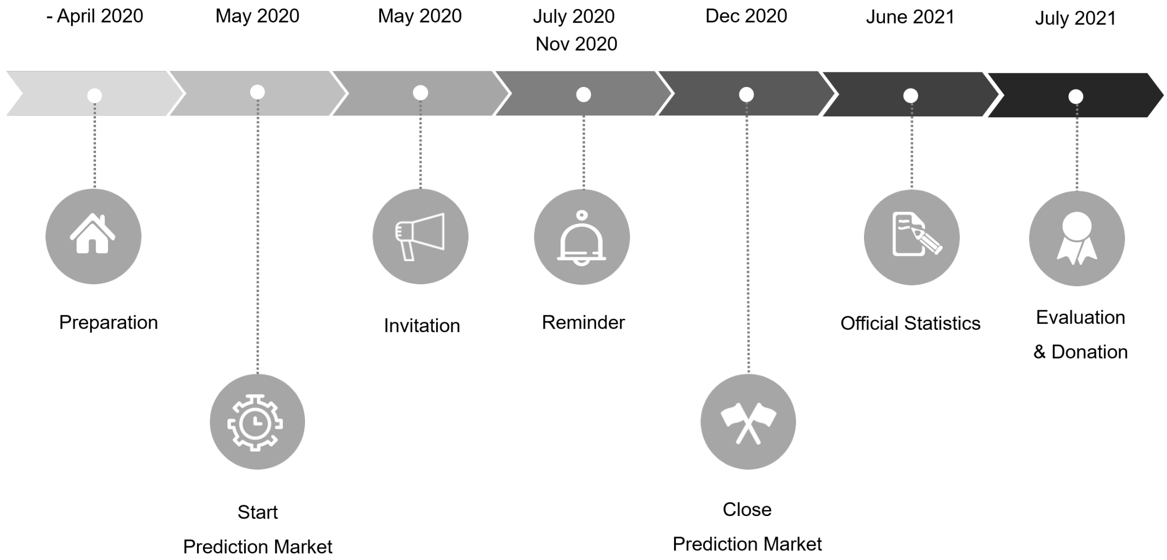
Appendices

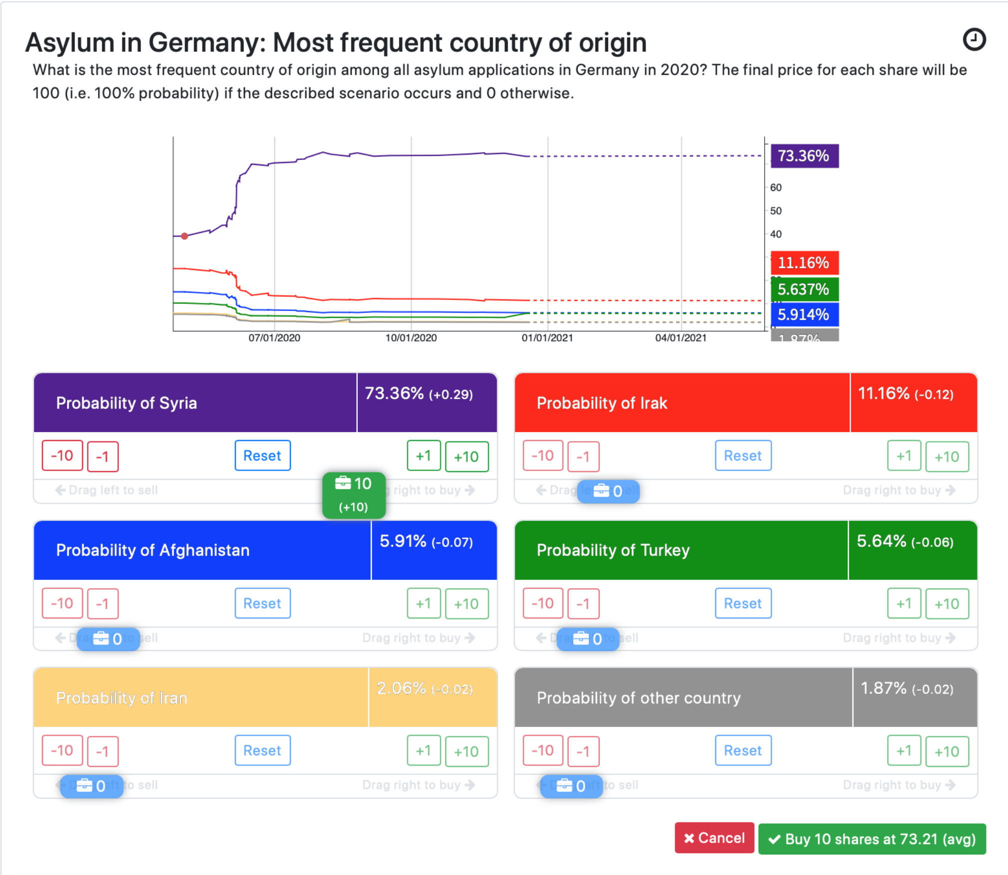
A. Study Design

Figure A.1: Timeline Study Implementation



B. Study Implementation

Figure B.2: Picture of a contract–set in the prediction market on migration flows



Notes

[1]Multiple terms with varying definitions are used in the literature of migration forecasting (Bijak et al. 2017; Sardoschau 2020; Sohst et al. 2020). This article uses the term ‘forecasting,’ indicating short-term forecasts (in contrast to ‘foresights’) into the future rather than the past (in contrast to ‘prediction,’ which often also covers projections into the past).

[2]Due to the LMSR’s logarithmic function, the algorithm works in such a way that it becomes increasingly expensive to push the price further down from the midpoint towards the minimum level, and equally increasingly expensive to push the price further up from the midpoint towards the maximum level. In a context of cash constraints, this could lead to the overpricing of contracts for which the expected final price is low and the underpricing of contracts for which the final price is expected to be high (Arnesen & Strijbis 2015). Since the final prices in a prediction market are linked to the outcome of the event, this translates directly into over- or under-predictions of the outcomes.

[3]This is of course only true if the trader has enough capital to conduct the trades and no other contracts deviate in the eyes of the trader more from the probability of the event taking place.

[4]The laymen sample was invited via email and the expert sample via email and additionally via postal mail.

[5]Among the laymen, we could draw on participants who have successfully participated in a previous prediction market on other topics like recent elections in Spain and Switzerland. These participants are also highly valuable because they understand the logic of the prediction market well and can exploit inefficiencies in the market, for example, through arbitrage gains.

[6]We counted 554 Emails sent to 223 participants of a prediction market on Spanish elections and 331 to participants of prediction markets on Swiss elections and direct democratic votes.

[7]See, for instance, the forecasts for the US presidential elections by Fivethirtyeight.com.