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The Stability of the Global Wheat Trade in the Post-Soviet Space: A Trade Duration Approach

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Abstract: The collapse of the Soviet Union and the Iron Wall as well as the emergence of Kazakhstan, Russia, Ukraine and Romania as major actors on international grain markets since 2000 had increased the hope for a more stable international grain market. However, various short-run trade policy interventions of post-Soviet grain exporting countries during the 2000s and 2010s have caused temporary disruptions in global grain supply chains. Moreover, the growing number of protectionist state interventions and sanctions since the beginning of the 2010s, as well as growing geopolitical tensions, may also fragment global trade and thus threaten the stability of grain trade relations. Against this backdrop and given the current public and political debates about suitable "de-risking strategies" to stabilise international trade, this article aims to explore the stability of the global wheat trade in terms of the duration dependence of trade relations between the major grain exporters and their destinations from 2001 to 2021. We test whether there are differences between the relatively "new" post-Soviet exporters that have emerged and the "old" ones. Furthermore, we examine the correlation between the number of trade partners and the trade duration. We employ a discrete-time hazard model to annual trade data to estimate the baseline hazard and survival rate for eleven major wheat exporting countries. The results indicate that, by having overall duration dependence, no different pattern in trade stability can be identified between "new" and "old" actors, and initial indications suggest that having more trading partners favours the survival of trade relations.

Keywords: Global Wheat Supply Chain, Trade Duration, Baseline Hazard, Logit, Kaplan-Meier Estimator, Survival Rate, Post-Soviet

1 Introduction

For the vast majority of countries, food security cannot be guaranteed by domestic production and the importing of different food and agricultural products is essential (Brenton et al., 2022). Recent studies show that approximately two-thirds of the world's population is dependent on imported foods (Kinnunen et al., 2020). The dependency on the grain trade has historical roots and is not a new phenomenon. For instance, historical records show that, as the Roman population increased, it became more dependent on wheat imports from other Mediterranean countries. Josephus recorded in his *Bellum Judaicum* that, in the late 70s A.D., North Africa (excluding Egypt) fed Rome for two-thirds of the year, while Egypt, in addition to providing financial resources for Rome, sent sufficient amounts of grain to feed the city for the rest of the year (Rickman, 1980). The shape of this trade has changed in modern times due to the discovery of the New World, grain cultivation in new regions and a drop in transport costs, which caused wheat prices to fall in the late 19th and early 20th centuries (O'Rourke, 1997). Tsarist

Russia was a major producer and exporter of grain before the Bolshevik Revolution in 1917 (Goodwin, Grennes, 1998). As its successor, however, the Soviet Union could never become the major wheat exporter that Tsarist Russia was, and it instead became a wheat importer. Grain imports from the Soviet Union were rather affected by geopolitics and the political economy, especially after World War II (Atkin, 1995). However, the post-World War II grain trade regime changed after the collapse of the Soviet Union due to structural changes to the agricultural systems in the new states in the post-Soviet space. With emerging wheat exporters such as Kazakhstan, Russia, Ukraine and Romania (collectively referred to as the ECA[1] wheat exporters in this study), the international wheat trade network was expected to become more stable and resilient (González-Esteban, 2018). However, the 2007-08 food crisis, followed by increased food price volatility, the COVID-19 pandemic and increasing geopolitical tensions since around 2020, such as the US-China trade conflict and the Russian invasion of Ukraine, have brought into question the stability and resilience of the international food network (Glauben, Duric, 2024), especially for grains (Glauben et al., 2022; Yugay et al., 2024).

Our analysis is motivated by two diverging issues: on the one side exporting and importing countries are exposed to the vulnerabilities of the international wheat trade network (Gutiérrez-Moya et al., 2021) and on the other side international trade relations also offer a safety net in the presence of climate or policy-related supply bottlenecks (Glauben, Svanidze, 2023). To investigate the stability of trade relations, we measure the temporal trade duration of the trade relations of the top eleven wheat exporters with their import partners from 2001 to 2021 and focus on two issues. Firstly, we look at whether the newly emerged ECA wheat exporting countries are showing remarkably different trade duration patterns compared to the historically established wheat exporting nations, such as the USA, Canada, Australia, Germany, France, the UK and Argentina. By selecting these top eleven major wheat exporters, the dynamic development in the international wheat market can be represented. Secondly, we explore whether there are differences in trade duration between exporters with a larger number of trading partners (i.e. more diversification) and those with a smaller number of trading partners (i.e. less diversification). The latter issue is particularly due to intensive recent debates in the political and public sphere about suitable “de-risking strategies” to secure supplies and thus the stability of trade relations (Glauben, Duric, 2024). On the one hand, it is argued that greater diversification, i.e. a large number of importing countries, reduces the risk of supply gaps via trade disruptions. At the same time and in contrast, it is argued that more stable international trade relations can be better achieved with a smaller number of selected and particularly reliable (“friendly”) trading partners and even self-sufficiency.

We apply a trade duration approach (Besedeš, Prusa, 2006a, 2006b; Hess, Persson, 2012) by estimating baseline hazard and survival rates for the wheat trade. Duration approaches complement the well-known gravity models (e.g. Anderson, 2011; Anderson, Yotov, 2012), as gravity approaches focus on the trading volumes but are not suitable for measuring the duration of trading relationships. Relatively long-term trade survival, i.e. high stability in the sense of comparatively few interruptions, between exporters and importers could be an additional indicator of well-established and robust wheat markets. Trade duration approaches are employed to examine and identify the stability of trade relationships (Córcoles et al., 2015; Obashi, 2010; Wang et al., 2019). When it comes to the substantial costs and risks of (re-)entering into and (re-)establishing new trade relationships, maintaining existing trade relationships might be crucial for the profitability of export and import partners. Additionally, rather longer-term trade relationships between partners could be a sign of higher vertical coordination and lower transaction costs (Ketokivi, Mahoney, 2020). Stable trade relations might allow agricultural and food producers in exporting countries to generate more revenues at lower risk and might ensure the availability of food products in importing countries (Engemann et al., 2022), particularly in the context of recurring market interventions and increasing geopolitical tensions. With a specific focus on the grain sector, we can observe the precise market conditions that lead (or can lead)

[1] Europe and Central Asia (ECA) is a categorization by the World Bank that refers to a list of countries in Southeast and Eastern Europe, the Caucasus and Central Asia: https://www.worldbank.org/en/region/eca

to unstable trade relations. Market conditions can be natural fluctuations of supply or demand over the years and at certain times. Fundamental market factors (such as weather events) rather than certain trade policies can be the cause of price formation and, as a result, can lead to changes in supply or demand. In certain years, when natural conditions are relatively good, importing countries can have high levels of self-sufficiency and may suspend imports, at least temporarily, as they are no longer dependent on them. Some countries have wheat self-sufficiency policies that may be in place for some years when there is higher rainfall (see Jaghdani et al. (2024a) for an example of the volatile wheat trade relationship between Russia and Iran). From the perspective of the exporting country, this can be considered an unstable trade relationship. From the perspective of the importing country, it is not necessarily the case. However, stable or long-term trading relationships are not a "gold standard" indication of the functionality of markets. For example, frequent changes between trading partners, i.e. rather *unstable* relations, could be a sign of a high level of adaptability and flexibility and could thus add to the functionality of markets.

This article explores several specifications of the trade duration model by distinguishing between the *single-spell* and the *multiple-spells* data structures in a discrete-time hazard framework that is estimated in a logistic regression. Furthermore, as a robustness test, we compare the estimated survival rate of the discrete-time hazard model with the traditional Kaplan–Meier estimator, which assumes continuous-time structures (Kaplan, Meier, 1958). This article is organised as follows: Section 2 presents background information on developments in the international wheat market, and Section 3 provides a literature review on food trade duration. In Section 4, the methodology and data are presented, while the results are presented in Section S before conclusions are drawn in Section 6.

2 Emerging ECA Wheat Exporters in the International Wheat Market

2.1 Structural Changes

Kazakhstan, Russia and Ukraine (KRU) were the three main wheat and coarse grain producing republics in the Soviet Union. However, on aggregate, the Soviet Union was a grain importer rather than an exporter (Fellmann et al., 2014). Upon the collapse of the Soviet Union, there was a huge drop in the size of agricultural production in the new-born republics and most of them turned into importers of many agri-food products. Later on, a series of economic reforms were started in their agricultural sectors, with these reforms having serious consequences, especially in KRU. During this transitional period, the institutions that had been left from the collectivisation of agriculture in the Soviet Union were transformed. Soviet agriculture was based on state-owned farms (Sovkhozy) and collective farms (Kolkhozy), which were demolished in the transitional period, and smallholder farmers with small to medium sized farms, large private farms or agricultural corporates emerged during this time. These agricultural corporates, often called agro-holdings, as well as large private farms, were able to increase productivity and efficiency, attract financial resources for investments, and integrate into international markets and global food supply chains. Downsizing the livestock sector was another change in this period. Through these structural changes observed since 1992, KRU became three major exporters of grains, oilseeds and feedstuff to international markets (Gafarova et al., 2015; Liefert, Liefert, 2015). Romania is another country which was a member of the former Socialist Bloc that has joined the top wheat exporters in recent years. It turned first into a wheat importer from 1990 to 1992, but, following a reform policy (FAO, 1993), Romania has since observed a total factor productivity increase in its agricultural sector (Tebaldi, Gobjila, 2018).

Figure 1 shows that Russia has transitioned from a country importing more than 13.5 million tonnes of wheat in 1992 to an exporting country with exports amounting to more than 40 million tonnes of wheat in 2018. Similarly, Ukraine, Kazakhstan and Romania also became major exporters.

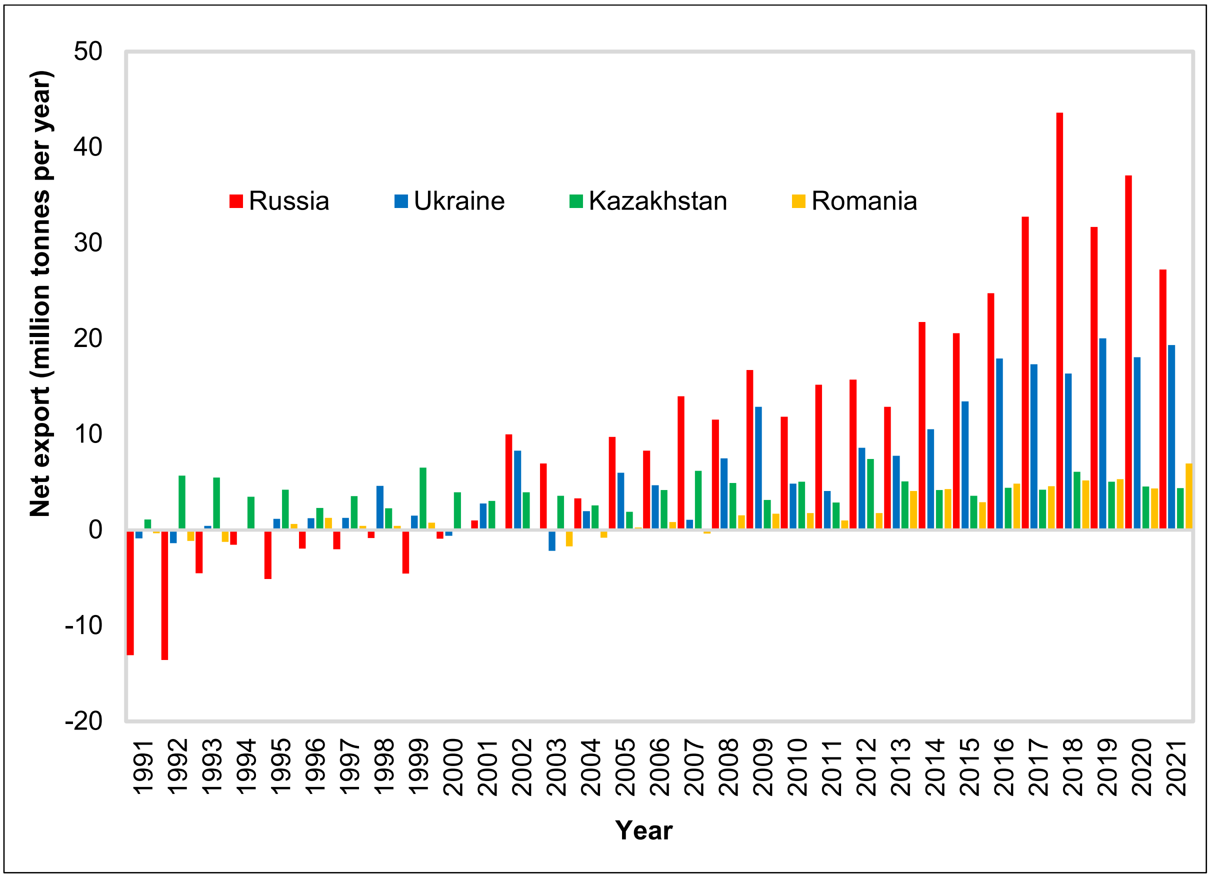

Figure 1. Net wheat exports from Russia, Ukraine, Kazakhstan and Romania (1991 to 2021)

Data source: UN Comtrade and Trade Map

The importance of agricultural exports is not similar but of noticeable economic importance for all four countries. For the 2017-2020 period, exports of agri-food products accounted for 42% of Ukraine's, 10% of Romania's, 6% of Russia's and 6% of Kazakhstan's total exports in value terms approximately. Specifically, for the same period, exports of wheat accounted for 7% of Ukraine's, 2% of Romania's, 2% of Russia's and 2% of Kazakhstan's total exports in value terms approximately[2]. The agricultural exports of these countries mainly consist of grains, oilseeds and oilseed oil. Figure 2 shows that Russia and Ukraine are among the top five and Kazakhstan and Romania are in the top eleven wheat exporters in the world. Since 2000, Russia was able to slightly pass the USA and become the largest wheat exporter in the world. In 2019, Russia, Ukraine, Romania and Kazakhstan accounted for 18%, 11%, 3.5% and 3% of world wheat exports, respectively.

[2] Data sources are UN Comtrade for wheat exports and WTO Statistics for agri-food and total exports (https://stats.wto.org/).

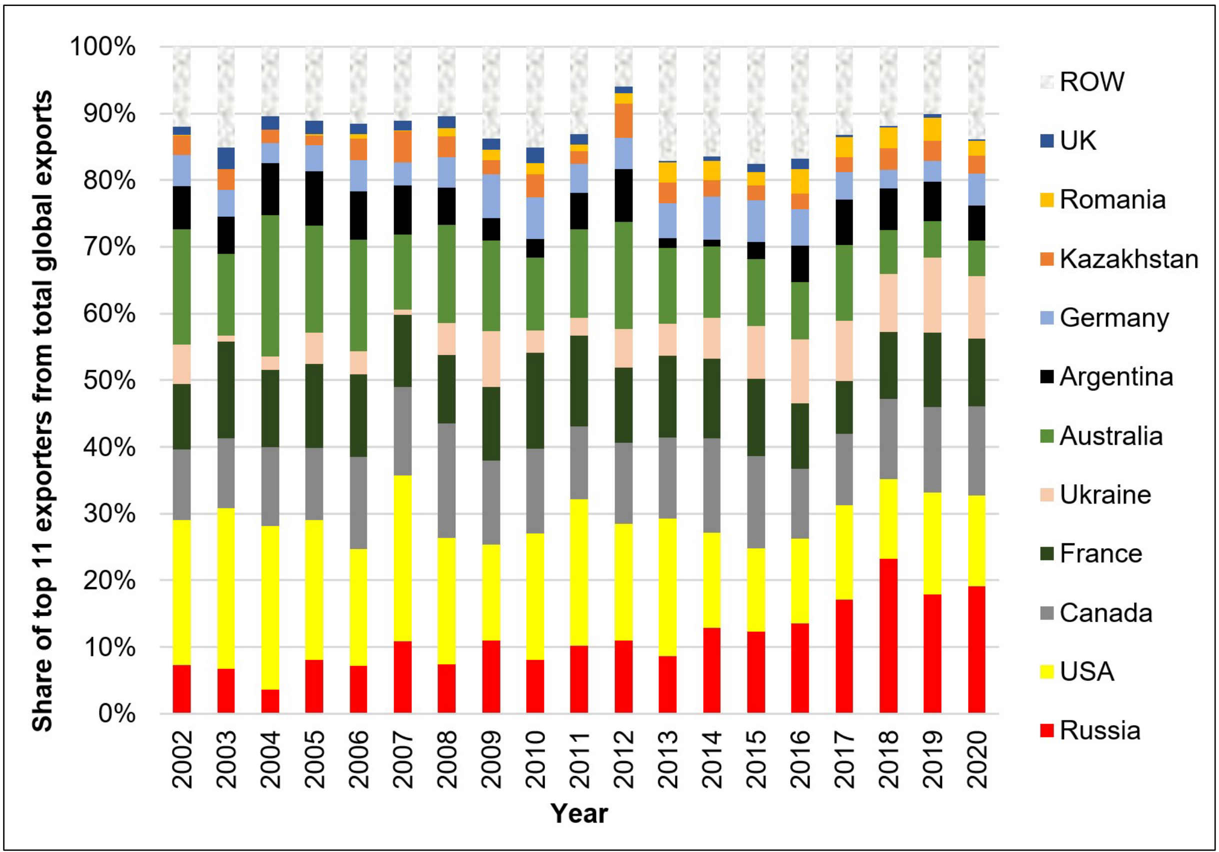

Figure 2. The share of wheat exports among the top 11 exporters for global wheat exports, 2001-2020 (HS Code: 1001)

Source of Data: UN Comtrade and Trade Map

By considering the average exports of wheat during the 2017-2020 period, Egypt, Indonesia, Bangladesh, the Philippines, Morocco, Tunisia, and Turkey were the main importers of Russian wheat while Egypt, Turkey, Bangladesh, Sudan, Nigeria, Yemen and Vietnam were the main importers of Ukrainian wheat. In the same period, politically unstable countries such as Lebanon, Libya and Ethiopia were on the list of wheat importers from both Russia and Ukraine. The processing and export of Russian wheat as flour has been observed among different countries in the Middle East and in particular Turkey (Heigermoser et al., 2022). For Kazakhstan, as it is a landlocked country, its main wheat export destinations are its neighbours, and, for the period of 2017-2020, Uzbekistan, Tajikistan, Afghanistan and China were the main importers of Kazakhstan's wheat (Gafarova et al., 2015). Egypt, Jordan, South Korea, Sudan and Israel are major importers of Romanian wheat[3]. Currently Kazakhstan, Russia, Ukraine and Romania are the biggest net wheat exporters of the former Socialist Bloc and have therefore been selected as new actors for this article. These countries faced many challenges in producing high-quality wheat in the post-Soviet space (Carson, Edwards, 2009). Although the quality of wheat can be determined by a range of factors, protein content is one of the main indicators. Durum wheat with a protein content of approximately more than 13% is suitable for pasta. Hard wheat with a protein content of approximately more than 13.5% is suitable for high-protein flour bread. With a protein content of 11.5% to 13.5%, it is used for flour bread. Soft wheat with a protein content of 8.5% to 9.5% is suitable for cakes, biscuits, puddings and pastry. Additionally, soft wheat with a protein content of 9.5% to 11.5% is a thickener and suitable for groceries. Mixed wheat types with a protein content of 9.5% to 11.5% are used in white Japanese and yellow Chinese noodles. Finally, mixed wheat types with a protein content

[3] Data source of wheat export destination: UN Comtrade (https://comtradeplus.un.org/) and Trade map (https://www.trademap.org).

of 10.5% to 12.5% are used for baking flatbread, which is common in the Middle East and North Africa (MENA) region (Wrigley, 2009). There is not much information available on the type of wheat exported by ECA wheat exporting countries. The little data available shows that the bulk of wheat exported from Russia, Ukraine and Romania has a protein content of between 11% and 12%, which makes it ideal for flatbread production in the MENA region (AEGIC, 2016a, 2016b; Marinciu et al., 2022). In addition to its lower price, this is a major reason why these countries export to the MENA region. In contrast, Kazakhstan produces higher-quality wheat, which is suitable for wheat flour (Altaibaeva et al., 2016). In 2021, Kazakhstan's durum wheat exports amounted to 3.8%. However, unlike Russia, Ukraine and Romania, Kazakhstan is a landlocked country with limited access to the international market (Svanidze et al., 2019). Therefore, wheat exports have remained relatively stable since 2001 due to transport costs. However, by expanding its flour-milling industry and producing higher-quality wheat for bread, Kazakhstan has increased its wheat flour exports to neighbouring countries (Altaibaeva et al., 2016). UN Comtrade wheat flour export data shows that, since 2005, Kazakhstan and Turkey have been the leading wheat flour exporters. Kazakhstan's maximum wheat flour export was 2.39 million tonnes in 2016. Similar to wheat, the flour is also mainly exported to Afghanistan, Uzbekistan and Tajikistan. However, because the focus of our article is on wheat, we avoid further analysis of wheat flour exports, as it is a different commodity.

2.2 Trade Policies

Since the emerging ECA exporters joined the global wheat export market, they have followed very unstable trade policies. Russia has repeatedly implemented export-related restriction policies (ERPs) for wheat (Svanidze et al., 2022), consisting of an export ban in 2010-11, and an export tax in 2007-08 as well as in 2015 (Figure 3). Since 2020 export quotas have been imposed temporarily, and since 2021 a flexible export tax system has been in place (Götz, Svanidze, 2023).

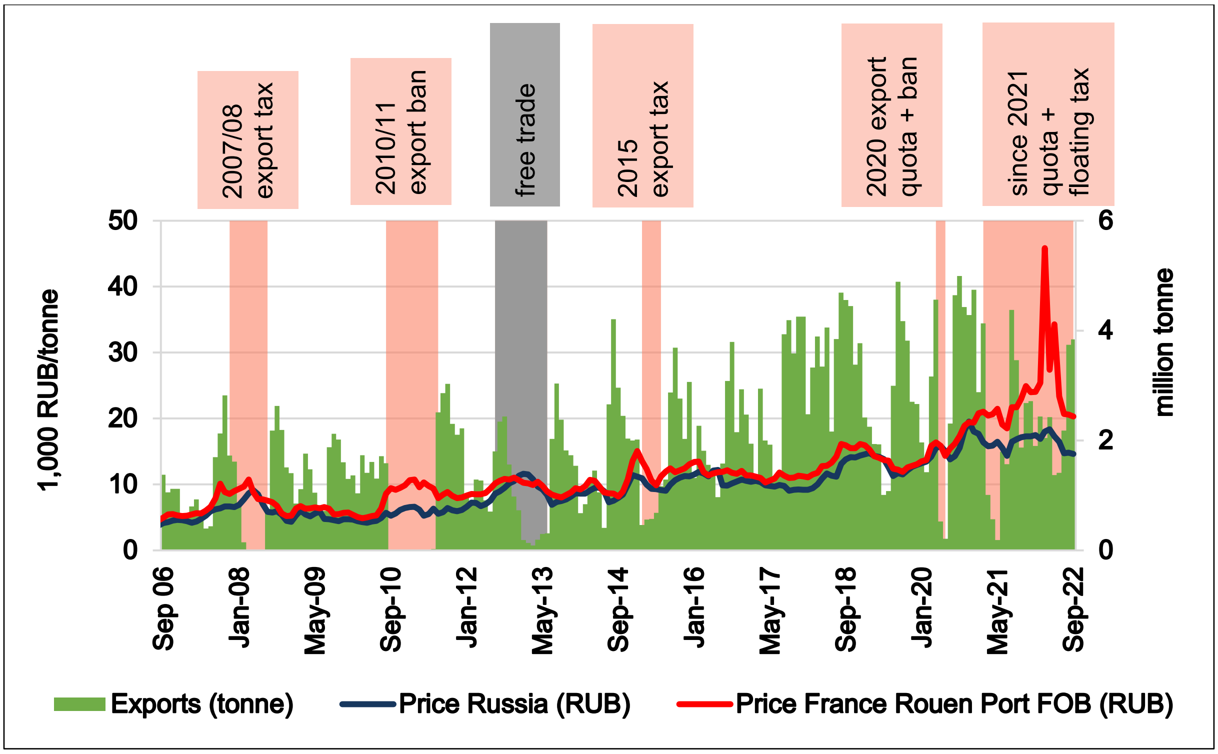

Figure 3. Russia's historical monthly wheat export development considering the trade policy volatilities and domestic and international prices in Russian ruble (RUB) (2006-2022)

Source: Götz, Svanidze (2023)

Ukraine has also implemented grain ERPs over the last two decades. For instance, from July 2007 to October 2007, Ukraine introduced a restrictive total grain export quota of 12,000 tonnes (3,000 tonnes each for wheat, barley, rye and corn), which essentially acted as an export ban. On another occasion, from October 2010 to July 2011, Ukraine implemented a grain export quota of 6.2 million tonnes for total grain exports. Further, from July 2011 to December 2011, export taxes were introduced. These were set at 9% for wheat, 12% for maize and 14% for barley (Fellmann et al., 2014). Additionally, Götz et al. (2013) found that rumours of export restrictions caused wheat price volatility in Ukraine's domestic market from 2005 to 2012. Kazakhstan also implemented grain ERPs, including an export ban from April 2008 to September 2008 (Fellmann et al., 2014). Further examples of grain ERPs can be found for Ukraine, Kazakhstan and a few for Romania[4]. Among the old actors, Argentina has had the highest number of ERPs since 2001 (AMIS, 2024). Australia also had a few registered export taxes and licensing requirements in place from 2003 to 2014. No further ERPs on wheat were found for wheat exports from the USA, Canada, the UK and the EU (AMIS, 2024).

3 Literature Review

The concepts of hazard or survival were mainly developed within the natural sciences, such as in biology and medicine (e.g. Cox, 1972; Kaplan, Meier, 1958), or, for instance, in labour economics and poverty research (e.g. Glauben et al., 2012). The "death" or loss of an object (or failure of an event) of a study was the main characteristic of time-to-event data in the natural sciences, for example, which "technically" (i.e. in terms of the model specifications) corresponds with an interruption in trade relations in trade duration models (Hess, Persson, 2012). Almost all trade duration studies lack a rigorous theoretical framework in the sense of consistent and clear behavioural assumptions (Engemann et al., 2022; Hess, Persson, 2011). The seminal works by Besedeš, Prusa (2006b, 2006a) build on reduced-form models by analysing trade duration for many commodities and countries. Trade duration models became theoretically founded with the introduction of the heterogeneous firm trade model by Melitz (2003). Consequently, extensive and intensive margins of trade were studied by considering a firm's heterogeneity (Besedeš, Prusa, 2011). On the other hand, trade duration models also underwent significant methodological advancements over the last decade. In particular, the discrete-time hazard model was introduced by Hess, Persson (2012), whereas, prior to that, the survival of trade relations was explored using the non-parametric Kaplan-Meier estimator (Kaplan, Meier, 1958) and COX proportional hazards model (Cox, 1972).

Most recent studies on the international agri-food trade duration specifically focus on perishable food items and the effects of trade policies and trade barriers. For instance, Peterson et al. (2018) find that sanitary and phytosanitary measures decrease trade duration, particularly in the first years of policy implementation for highly perishable fruit and vegetable products in the US. Likewise, Luo, Bano (2020) investigate New Zealand's dairy exports and trace back the decreasing likelihood of continuous trade relationships to technical barriers to trade implemented by importing countries. A particular and novel strand of the trade duration literature focuses on the analysis of the seafood trade, for which perishability is an even more critical issue (e.g., Jaghdani et al., 2024b).

With the improvements in the availability of firm-level trade transaction data, the number of trade duration studies conducted at the firm level also increased, but they are still rare. For instance, Gullstrand, Persson (2015) find the trade duration of food items for Swedish firms to be higher in core markets (the firms' primary export destinations) than in peripheral markets (the firms' minor export markets). In another study, Jaghdani et al. (2024) apply a heterogeneous firm trade model (Melitz, 2003) to firm-to-firm trade transaction data on the salmon trade, finding that the salmon trade duration is relatively short-lived (around 2.5 years on average).

[4] The records of different export restrictions can be followed via the Global Trade Alert (GTA) platform: https://www.globaltradealert.org/.

Although the EU is a major importing market for Norwegian salmon, they found that the stability of trade between different partners is not huge for major and minor importing markets or different continents.

To the best of our knowledge, Imamverdiyev et al. (2015) and Jaghdani et al. (2020) are the only studies that analyse the duration of wheat exports. Imamverdiyev et al. (2015) exclusively focused on Kazakhstan. They concluded that the trade duration of Kazakhstan's wheat exports can be explained by high trade costs, the use of local production factors, and a lack of price competitiveness and experience. By focusing on France, Jaghdani et al. (2020) observed more stable trade relations between France as the exporter and other EU importing countries compared to non-EU importing countries. In contrast to the available literature, this article is the first comparative study to focus on the analysis of trade duration for the largest eleven wheat exporting countries. Moreover, this study also makes a methodological contribution to food trade duration studies by estimating the survival function of each wheat exporter through a discrete-time hazard model (Hess, Persson, 2012).

4 Methodology and Data

In this Section, we first present the discrete-time hazard model building on Hess, Persson (2012), Peterson et al. (2018) and Engemann et al. (2022). However, the empirical approach in this study is limited to estimating the baseline hazard model (Tutz, Schmid, 2016) and the corresponding survival function. Second, as a robustness test, we compare the results of the novel discrete-time estimator to the standard classical non-parametric Kaplan-Meier survival estimator, which is presented in the subsequent Section. Last, we discuss the estimation strategy and data structure.

4.1 Baseline Hazard Model

We start by defining a spell of trade. A spell of trade (i, $i=1,\ldots,n$) is defined as the realisation of the trade relationship for a period with uninterrupted trade of a product between an exporter country X and an importer country M (Besedeš et al., 2023). The duration of each spell (T_i) is then defined as the number of consecutive years with non-zero trade between partners. Let T_i be a non-negative, continuous random variable that measures the survival time of the ith trade relationship without interruption (or ith spell). Next, we define a set of discrete-time intervals [t_1, t_2,.., t_k, … t_{max}] when $k=1$ means $t_k = t_1 = 0$ and $1 \leq k < max$. The probability that the ith trade relationship (or ith spell) ends in t_kth time interval is conditional on the uninterrupted trade relationship (or spell) surviving up to the beginning of that time interval and on a set of explanatory variables in the model. When trade failure happens in a particular discrete time interval [t_k, t_{k+1}), then the duration of each spell or $T_i = t_{k+1}$ (Tutz, Schmid, 2016, chapter 3). This means that the duration of the trade spell is the length of time the individual trade relation existed, usually recorded as the last period in which the trade is observed (Singer, Willett, 1993). As suggested by Hess, Persson (2012), in the discrete-time hazard model, trade duration is estimated as a conditional probability that the trade of a product will terminate in a particular discrete time interval [t_k, t_{k+1}) defined above ($1 \leq k < max$). This conditional probability of trade interruption, which is also defined as a discrete-time hazard rate (h_{ik}), can be formulated as follows:

$$h_{ik} = h(t|\boldsymbol{x}) = P(T_i < t_{k+1}|T_i \geq t_k, x_{ik}) \tag{1}$$

$$= F(\gamma_k + \boldsymbol{x}'_{ik}\boldsymbol{\beta})$$

where $\boldsymbol{x}'_{ik}$ is a vector of time-varying covariates, $P()$ is conditional probability and $\boldsymbol{\beta}$ is a vector of coefficient parameters that should be estimated. Furthermore, γ_k is the baseline hazard as a function of time allowing the hazard rate to vary across time intervals and *F* is the appropriate probability distribution function ensuring $0 \leq h_{ik} \leq 1$.

Because the baseline hazard rate is unknown, γ_k is incorporated in the empirical model as a set of dummies that identify the duration of each spell. In the estimation procedure, we let y_{ik} be a binary variable that is equal to one if the spell *i* ends (i.e., if trade terminates or fails) in the time interval $[t_k, t_{k+1})$ and zero otherwise (i.e., if trade occurs). Now, the discrete-time hazard model in Equation (1) can be estimated by log-likelihood function as:

$$ln\mathcal{L} = \sum_{i=1}^{n}\sum_{k=1}^{k_i}[y_{ik}ln(h_{ik}) + (1 - y_{ik})ln(1 - h_{ik})] \quad (2)$$

To obtain consistent parameter estimates, each spell must be independent of all other spells, which is comparable to the independence of irrelevant alternatives assumption in logit models. Therefore, we control for multiple spells and any dependencies across wheat exports by each exporter or across exporters and importers. Considering the assumed distribution for Equation (2), any type of a generalised linear model (GLM) can be applied for estimating Equation (2) by having the correct link function $g(.)$, for example, logit function $log(.)$, defined as Equation (3):

$$g\big(h(t|\boldsymbol{x})\big) = log\left(\frac{h(t|\boldsymbol{x})}{1 - h(t|\boldsymbol{x})}\right) = log\left(\frac{P(T = t|\boldsymbol{x})}{P(T > t|\boldsymbol{x})}\right) = \gamma_t + \boldsymbol{x}_{it}^{'}\boldsymbol{\beta} \quad (3)$$

Therefore, the hazard rate for logit functional form can be defined as Equation (4):

$$h(t|\boldsymbol{x}) = \frac{\exp(\gamma_t + \boldsymbol{x}_{it}^{'}\boldsymbol{\beta})}{1 + exp\big(\gamma_t + \boldsymbol{x}_{it}^{'}\boldsymbol{\beta}\big)} \quad (4)$$

If we do not consider any covariates (or $\boldsymbol{x} = 0$), then the hazard model reduces to the baseline hazard model $h(t|\mathbf{0})$, which is estimated in this study, as follows (Tutz, Schmid, 2016, chapter 3):

$$h(t|\mathbf{0}) = \frac{\exp(\gamma_t)}{1 + \exp(\gamma_t)} \quad (5)$$

4.2 Survival Function

By having the baseline hazard estimated through Equation (5), we can calculate the survival function, which is inversely related to the baseline hazard rate. The survival function that is denoted by $S(t|\boldsymbol{x})$ is the probability of an individual surviving all time intervals at least until time *t* (this is the same *t* as in Equation (1)), where $0 \leq S(t|\boldsymbol{x}) \leq 1$ (Johnson, 2018). Therefore, $S(t|\boldsymbol{x})$ of a spell of length *T* for each trade spell *i* can be determined through Equation (6) (Tutz, Schmid, 2016, chapter 3):

$$S(t|\boldsymbol{x} = \mathbf{0}) = P(T > t|\boldsymbol{x} = \mathbf{0}) = \prod_{j=1}^{t}\big(1 - h(j|\boldsymbol{x} = \mathbf{0})\big) \quad (6)$$

Where *j* is the duration of each spell and lies in between one and *t.*

4.3 Kaplan-Meier Estimator of Survival Function

It is mentioned above that one of the objects of interest in this study is a measure of survival of exports of wheat by country X to another country M. As explained in 4.1, we use T_i in discrete-time hazard analysis as a non-negative random variable representing the failure time (or the time until trade cutting occurs) after period t of an individual ith trade relationship (or ith spell) from the homogeneous population. However, the survival function can also be estimated by assuming the time is observed on a continuous scale. Instead of defining the statistical model for the response T_i in terms of the expected failure time, it is advantageous to define the survival function, $S_i(t)$ as:

$$S_i(t) = Prob\{T_i > t\} = 1 - F_i(t) \tag{7}$$

where $F_i(t)$ is the cumulative distribution function. If the event is wheat trade failure, $S_i(t)$ is the probability that wheat trade failure occurs after period t, that is, the probability that the subject of trade relations will survive at least until time t. $S_i(t)$ is a non-negative right-continuous function of t with $S(0)=1$ meaning all subjects survive at least to $t=0$. The survival function must be non-increasing as t increases.

Building on a non-parametric estimate of a survival function $S(t) = P(T > t)$ by assuming the time is observed on a continuous scale as given in Equation (7), the Kaplan-Meier estimator (also named as product-limit estimator) is defined as:

$$\widehat{S(t)} = \prod_{j=1}^{t} \frac{n_j - d_j}{n_j} \tag{8}$$

where n_j is the total number of objects (trade relations or trade spells in this case) at risk at time j, and d_j is the number of failures of trade at time j. This estimator is a standard robust measure in survival analysis. The notation j in Equation (8) is the same as in Equation (6). However, similar to the baseline hazard model, this estimator does not address the relation between the survival rate and potential covariates.

4.4 Estimation Strategy

Our estimation strategy consists of two steps. First, the trade data are employed to establish the trade spells in both discrete-time and continuous-time structures. Furthermore, for both discrete-time and continuous-time datasets, two different *single-spell* and *multiple-spells* data structures are also defined and tested, which are specifically explained in the data section. After retrieving the dataset, the discrete-time data structure is employed to estimate the baseline hazard model (see Equation (5)) through a logistic regression from the GLM family. By having the parameter γ_t from Equation (5) estimated, the baseline hazard rate or $h(t|\boldsymbol{x} = \mathbf{0})$ from Equation (5) is determined, which is used to calculate the survival function ($S(t|\boldsymbol{x} = \mathbf{0})$) in Equation (6). In the case of the Kaplan-Meier estimator (see Equation (8)), the prepared continuous-time data structure is employed to estimate the empirical survival function ($\widehat{S(t)}$).

4.5 Data

We used wheat trade data from the UN Comtrade and Trade Map databases to extract the trade spells. In order to ensure that only durum, soft, hard red spring and winter wheat are considered in the dataset and that seed wheat trade is excluded, the six-digit harmonised system (HS) commodity codes of durum wheat (100110 & 100119) and non-durum wheat (100190 & 100199) are used. Total aggregated annual wheat trade volumes smaller than 50 tonnes per annum were not considered as active trade relations. Finally, the aggregated data from the four categories is used to establish the data structure as presented in Figure 4.

We considered the appropriate censored structure for establishing the database for those trade relations that do not end by 2021 (see cases B, D and F in Figure 4). Furthermore, we distinguished between the cases A, B, C and D for the *single-spell* trade relation and the cases E and F for the *multiple-spells* trade relation, as presented in Figure 4. If trade between partners is one continuous and uninterrupted trade data series over the entire time period of our consideration, we identified such trade relations as a *single-spell* data structure. However, we distinguish between two cases for data with initial interruptions in trade relations followed by subsequent single or multiple revivals and interruptions in the later periods (see Figure 4, case E and F). In the first case of the *multiple-spells* data structure, we consider the revival of trade relations between two partners after a prior interruption between 2001 and 2021 as a new spell, which corresponds with the restarting of the time interval for the trade duration (t_1=0 is assigned to each new restart of the trade relation). Alternatively, we consider the same *multiple-spells* data arrangement as a *single-spell* data structure by ignoring the interruption of trade relations between partners and treating the revived trade relations as a continuation of the previously started trade relations with respective uninterrupted sequencing in time interval numbering (*t* is always increasing).

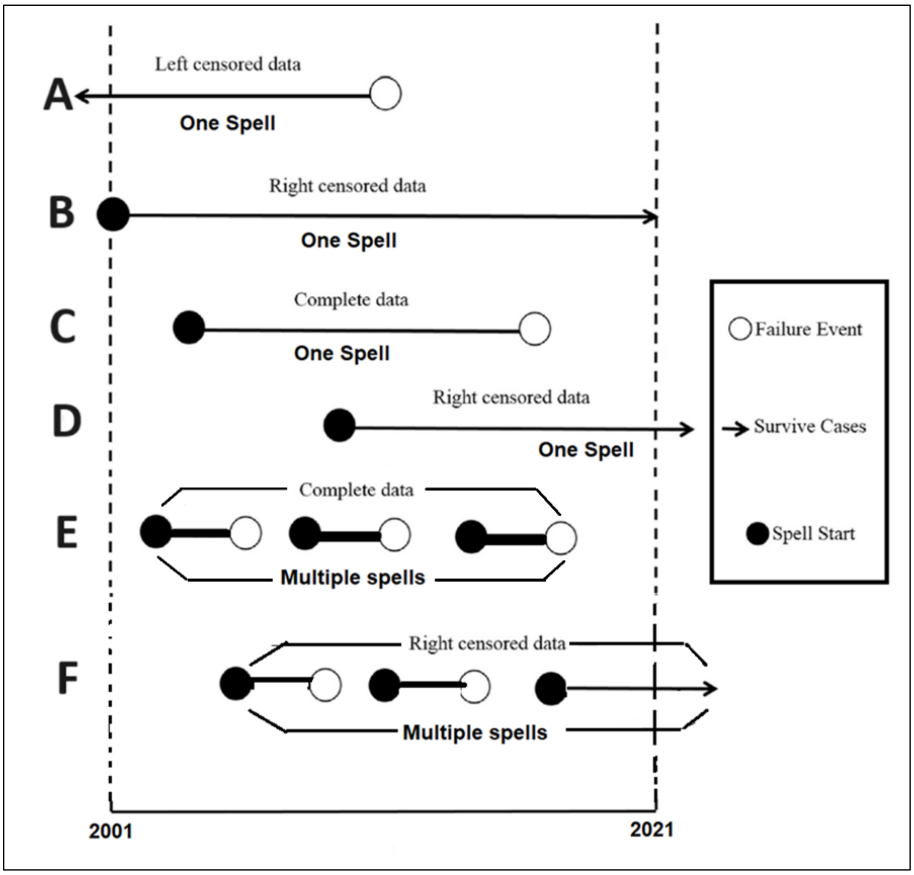

Figure 4. Trade data structure for duration analysis

Source: Lee et al. (2020) with modification

5 Results and Discussion

5.1 Summary Statistics

Exclusively focusing on observations from the *multiple-spells* data structure[5], Table 1[6] shows the number of trade partners, trade spells and average spell per partner by exporting country over the study period from 2001 to 2021. The USA and the UK have the highest (152) and lowest (50) number of importing partners respectively. However, the countries with fewer destination markets are not necessarily the ones with the most frequent trade interruptions at the bilateral level (i.e. a high value of the average trade spells per import country). For instance, with 89 trade partners, Australia has the lowest average trade spell per destination market (1.72), and hence is characterised by having the most uninterrupted trade relations. In contrast, trade interruption and subsequent revival is more common for Germany, Russia and Ukraine, with a relatively large number of trade partners (between 120 and 141), as their average trade spell per partner lies between 2.19 and 2.46. Similarly, Kazakhstan and Romania also register higher values for the average trade spell per partner (2.31 and 2.36, respectively), however, their number of partners is relatively smaller, with 71 and 84 destination markets, respectively. In a nutshell, while there are large differences in the number of trading partners and the frequency of trade disruptions in the global market, the values of bilateral trade disruptions are around 2 for all exporters and are very similar. Therefore, we can cautiously conclude that all wheat exporters ("old" or "new") have, on average, quite stable bilateral trade patterns.

Table 1. Number of trading partners, trade spells and average trade spells per partner for the top 11 wheat exporting countries for the 2001-2021 period

	Exporting countries										
	Old actors							**New actors**			
	USA	Canada	France	Australia	Argentina	Germany	UK	Russia	Ukraine	Romania	Kazakh-stan
No. of trading partners	152	133	128	89	96	120	50	141	130	84	71
No. of trade spells	295	260	252	153	241	268	101	309	320	198	164
No. trade spells per importing partner	1.94	1.95	1.97	1.72	2.51	2.23	2.02	2.19	2.46	2.36	2.31

Source: study findings

Table 2 shows that the one-spell trade relation is the most prevalent trade structure between exporters and importers. Furthermore, we can see that, by and large, all 11 exporters experience mostly only one or two interruptions in their bilateral trade relations (by having one or two, short or long, spells) with individual target countries, indicating once more relatively robust conditions. In addition, the prevalence of the one-spell structure is inversely related to the average number of spells per import country. For example, similar to Table 1, with 58.4%, Australia has the highest one-spell (uninterrupted) trade relations structure with its partners and Argentina, with 27.1%, has the lowest one-spell (continuous) trade structure with its partners. Among the ECA exporters, with 39.6%, Russia has the highest one-spell structure and Ukraine

[5] Throughout the Subsections 5.2 and 5.3, we provide enough evidence and arguments in favour of a *multiple-spells* data structure versus a *single-spell*.

[6] The order of the exporters in all tables in this article from left to right is based on the reducing amount of total wheat exports during 2019-2021 in two separate blocks of old actors and new actors.

has the lowest (30.0%). The USA and France also have more than 50% of their trading partners with a one-spell trade data structure.

Table 2. Distribution of the number of importing partners with different numbers of spells and the average survival time of trade spells for the multiple-spells data structure of the top 11 wheat exporters for the 2001-2021 period

		Exporting countries										
		Old actors							New actors			
	No. of spells	USA	Canada	France	Australia	Argentina	Germany	UK	Russia	Ukraine	Romania	Kazakhstan
Number of importing partners with different number of t spells	1	78	66	64	52	26	49	23	57	39	27	25
	2	29	29	25	18	28	22	12	44	34	20	21
	3	27	22	24	13	19	22	6	22	28	20	11
	4	14	11	11	4	14	18	5	11	20	9	7
	5	2	4	2	2	8	5	2	6	6	7	6
	6	2	1	2	0	1	2	1	4	2	0	1
	7	0	0	0	0	0	0	0	0	1	0	0
Average survival time (years)		6.44	7.05	5.76	7.07	3.29	4.51	3.51	6.59	4.71	4.24	4.04

Source: study findings

By using the data on the number and length of the spells and employing the "restricted mean survival time" estimator, we find that the average survival length of trade spells is between 7.07 years for Australia and 3.29 years for Argentina for the *multiple-spells* data structure for the period 2001-2021 (see Table 2). Without wishing to overinterpret this, the values do not indicate that the "old" exporters interrupt their (bilateral) trade relations after longer periods on average than the "new" ECA actors, i.e. KRU and Romania.

Summing up, the results of Table 1 and Table 2 do not show clear clusters considering the number of partners, spells and trade breaks between the "old" and "new" actors. However, the length of spells and the number of importing partners show a trend that is worthy of further exploration. By using the trade data presented above and employing the discrete-time baseline hazard and Kaplan-Meier estimator as explained in Section 4, the survival rates in two different ways are estimated, which is provided in the following subsections.

5.2 Survival Rates (Discrete-Time Hazard Model)

The baseline hazard rates are estimated from the logistic regression (Equation (5)) with 21 dummy variables representing the 21 different spell lengths (see Table A1 and Table A2 in the Appendix)[7]. As Romania is a rather new actor in the world market, its longest undisrupted trade spell in the *multiple-spells* data structure is 18 years and in the *single-spell* data structure is 20 years. For a straightforward comparison, we have discussed the survival rates of a spell length of 18 years. The results of the logistic regression show that we cannot reject the temporal

[7] The results of the multiple spells/single spell logit regressions estimation for each exporter are not presented here but are provided in the Appendix. They consist of two blocks of logit model estimations, each consisting of 11 equations with 21 parameters (γ) for the maximum 21-year length of the spells (see Equation (1) and Equation (5)). As explained in Section 5.2, Romania doesn't have 21-year spells. Therefore, the maximum number of estimated parameters is 18 for the *multiple-spells* data structures and 20 years for the *single-spell* data structures.

dependence of the trade relations of the major wheat exporters with their import partners. Further, Figure 5 and Figure 6 show the survival rates ($S(t|\boldsymbol{x} = \mathbf{0})$) estimated separately for the *multiple-spells* and *single-spell* data structures, respectively, using the baseline hazard rates retrieved from the logistic regression. Comparing across different spell structures, we observe that, although the magnitude of the survival rates differs, the direction of changes with the increasing spell length (in years) is comparable. In particular, survival rates are larger with the *multiple-spells* structure compared to the *single-spell* structure, however, they are lowest at the maximum spell length (21 years) in both spell structures (compare Figure 5 and Figure 6). Table 3 compares the survival rates for spells of 11 and 18 years between the *multiple-spells* and *single-spell* data structures. For instance, by taking Russia as an example, in Table 3, we can observe a survival rate of 22.8% and 10.5% in the *multiple-spells* and *single-spell* structures at a spell length of 11 years, respectively. Russia's survival rates drop from 19% to 7.6% in the *multiple-spells* and *single-spell* structures at a spell length of 18 years.

Comparing Figure 5 and Figure 6, it becomes evident that the different datasets for both the *single-spell* and *multiple-spells* have similar survival patterns. However, the survival rates of exporters with a lower number of partners at longer spells have dropped dramatically, especially in the *single-spell* data structure. Since the results are quantitatively comparable across the *single-spell* and *multiple-spells* structures, we limit the discussion of results to the survival rates estimated for the *multiple-spells* structure (Figure 5). Therefore, we find that, for a survival time of up to 18 years, Canada and Australia have the highest survival rates, with 22.7% and 22.2% respectively, and Argentina has the lowest survival rate, with 2.5%. Canada and Australia both export significant quantities of durum wheat and high-quality wheat. This may suggest that their higher survival rates are due to wheat quality. Moreover, their partners have especially strong preferences for durum wheat and other high-quality wheat varieties that are used for blending purposes. For instance, in 2021 durum wheat accounted for 21% and 1.7% of total wheat exports of Canada and Australia, respectively. Nevertheless, Australia also exports non-durum, high-quality wheat varieties that are preferred for baking and for Asian noodle purposes in particular (Miskelly, 2019). Canada's and Australia's survival rates are followed by the USA and Russia, which also mainly export wheat for baking purposes, showing similar survival rates for the survival time of up to 18 years of around 19% in *multiple-spells* settings. As the major wheat exporter of Europe, France has a survival rate of 16% for the survival time of up to 18 years. This can be due to lower quantities compared to the USA and Russia. With trade spells of up to of 21 years, this group of five exporters (Australia, Canada, the USA, Russia and France) can be categorised as a higher survival rate cluster. The common feature of this group is also their sizeable wheat exports.

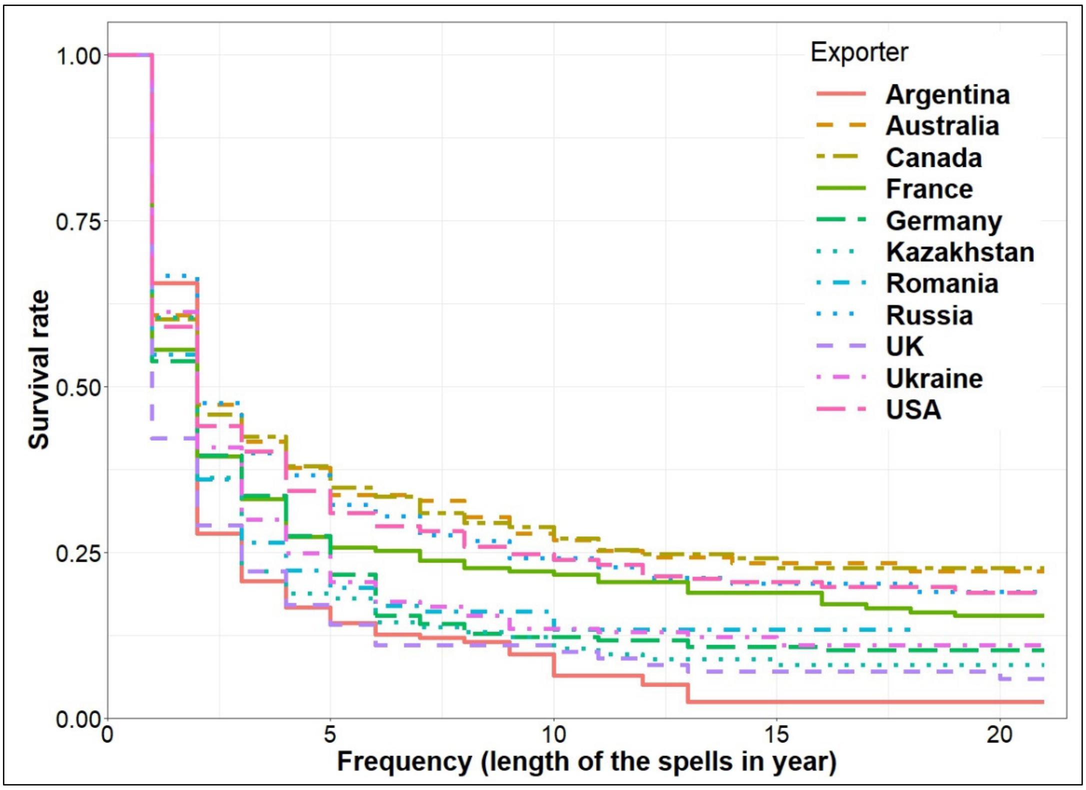

Figure 5. Survival rates for trade spells between each exporter and all their partners (multiple-spells data structure)

Source: study findings

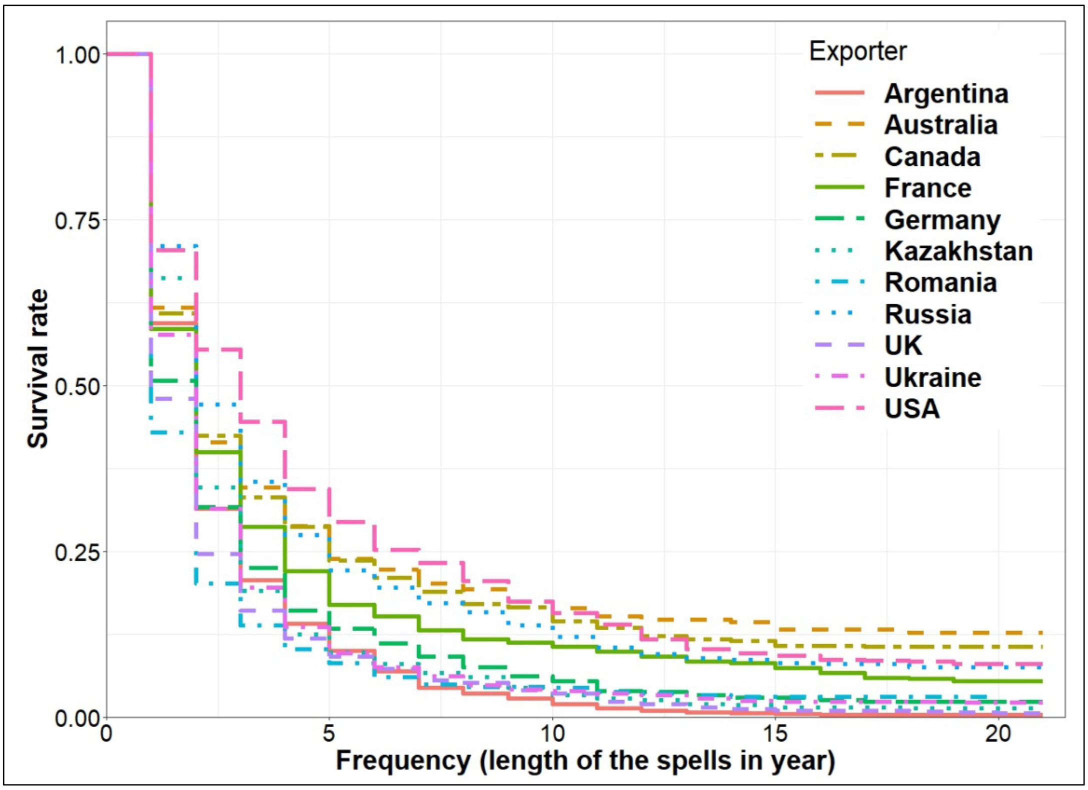

Figure 6. The survival rate for trade spells between each exporter and all its partners (single-spell data structure)

Source: study findings

Based on spells with a duration of up to 18 years, the survival rates amount to 13%, 11% and 10% for Romania, Ukraine and Germany, meaning they are “medium survival rate” exporters. As Romania is a rather new actor in the world market, the dataset is limited to 18 years. However, its survival rate of up to 18 years is similar to that of Ukraine and Germany. Ukraine and Romania have similar (and even slightly higher) survival rates compared to an established actor such as Germany. The UK, with a 7% survival rate, and Kazakhstan, with an 8% survival rate, have similar patterns considering the 18 years of the longest trade spell in the *multiple-spells* setting. UK wheat exports are declining and mainly consist of fodder wheat (Fradgley et al., 2023), which competes with other feedstuff. Kazakhstan has limited export possibilities due to its geographical landlocked conditions and thus limited access to the world market (Svanidze et al., 2019). If Kazakhstan restricted its wheat exports to only a few neighbouring countries, it could have a higher survival rate, as higher volumes could be traded with fewer partners and each partner would become more important. Nevertheless, as Kazakhstan exports to countries that are further away, more unstable, short-lived trade spells appeared that reduced its survival rate. With 2.5%, the lowest survival rate after 18 years of trade is found for Argentina. This rather low rate could result from unstable export trade policies, unstable exchange rate policies, periodically high domestic inflation or regular implementation of ERPs.

Table 3. Survival rates of the two data structure (*multiple-spells* and *single-spell*) estimation frameworks for comparison at the spell length of 11 and 18 years using the discrete-time hazard model

		Survival rate retrieved from logit estimation for spells of length 11			**Survival rate retrieved from logit estimation for spells of length 18**		
	Countries	*Multiple-spells* data	*Single-spell* data	Diff*	*Multiple-spells* data	*Single-spell* data	Diff*
Old actors	USA	0.231	0.140	0.091	0.198	0.084	0.114
	Canada	0.254	0.135	0.119	0.227	0.106	0.121
	France	0.206	0.099	0.107	0.16	0.058	0.102
	Australia	0.252	0.152	0.100	0.222	0.127	0.095
	Argentina	0.064	0.014	0.050	0.025	0.004	0.021
	Germany	0.118	0.040	0.078	0.103	0.024	0.079
	UK	0.090	0.024	0.066	0.07	0.009	0.061
New actors	Russia	0.228	0.105	0.123	0.19	0.076	0.114
	Ukraine	0.130	0.036	0.094	0.11	0.024	0.086
	Romania	0.134	0.038	0.096	0.134	0.031	0.103
	Kazakhstan	0.097	0.028	0.069	0.08	0.014	0.066

*Diff measures the difference between survival rates of the *multiple-spells* and *single-spell* data structures
Source: study findings

The results of the estimated survival rates through the discrete-time hazard model can be cautiously summarised as follows: Initially, we cannot see different types of clusters among the “new” and “old” actors. Subsequently, it seems that the largest exporters (namely the USA, Russia, Canada and France), both in terms of the amount of wheat traded and the number of trading partners, have the highest survival rates. Furthermore, high wheat quality could encourage long-lasting bilateral trade relations (e.g., Australia and Canada). Moreover, limited market access, such as in Kazakhstan as a landlocked country, seems to work against long-lasting trade. In the context of the logit estimator, survival rates with a *single-spell* structure are substantially underestimated. This issue is further tested and discussed in Section 5.3.

To visualize the relationship between survival rates and the number of trading partners, we have plotted the number of importing trading partners of each exporter (as an indicator of diversified partners) versus the average length of spells of each exporter (see Section 5.1) and the survival rate of the 18-year spell (see Figure 5 and Table 3). The results of this depiction, which should be viewed very conservatively due to the low number of observations, show that there is a pattern between the average length of spells of each exporter and the number of partners (see Figure 7, panel A), with a correlation coefficient of 63% at 5% significance. We can also recognise a rising correlation (with a correlation coefficient of 56% at 10% significance) between survival rates and the number of partners (see Figure 7, panel B). The result shows that, on average, exporters with more trading partners also have more stable trade relations. This may result in long-term bilateral relations with many individual trading partners, as exporters can switch between individual partners and therefore quickly find a "new" buyer in the overall world market. Hence, stability in the overall pool of destination markets can be achieved either by (a) flexible adaptation or (b) continuity of individual relationships.

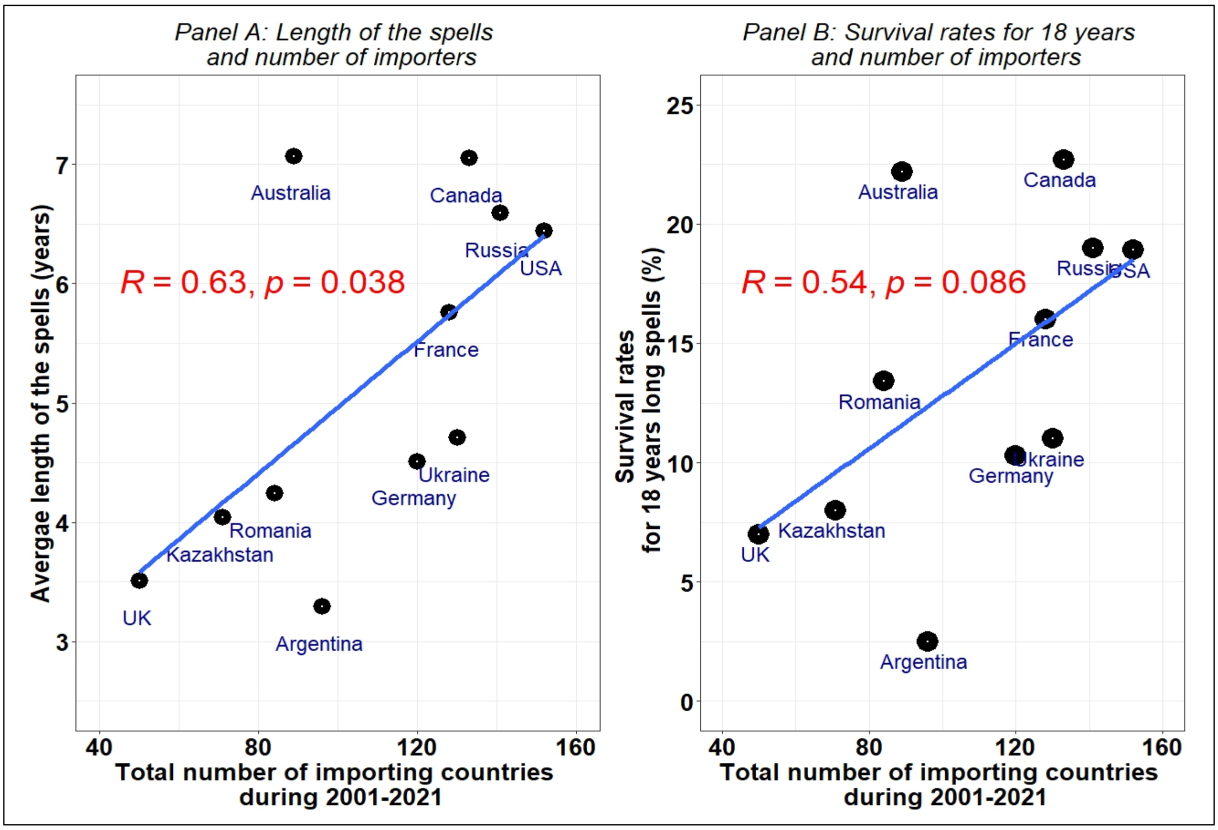

Figure 7. The relationship between the number of trading partners, the average length of the spells and the survival rate of the 18-year spells

Source: study findings

5.3 Robustness Test of the Survival Rates with the Kaplan-Meier Estimation and Study Limitations

Figure 8 and Figure 9 show the estimated survival rates using a non-parametric Kaplan-Meier estimator for the *multiple-spells* and *single-spell* structures, respectively. In the *multiple-spells* structure, survival rates as well as their patterns are nearly identical across the Kaplan-Meier estimation method and the discrete-time hazard model with the logistic regression approach (compare Figure 5 and Figure 8). In contrast, the survival rates of the Kaplan-Meier estimator are higher in every instance with the *single-spell* structure (compare Figure 6 and Figure 9). Additionally, the pattern of survival rates in Figure 9 is different compared to all other estimators (Figure 5, Figure 6 and Figure 8). For ease of interpretation, Table 4 compares the survival rates derived from the Kaplan-Meier estimator for spells of 11 and 18 years between the *multiple-spells* and *single-spell* data structures. For instance, in the *multiple-spells* structure, Russia has a survival rate of 22.8% at the spell length of 11 years, which decreases to 19% at the spell length of 18 years, whereas the comparable changes are 62.1% and 52.2% in the *single-spell* structure, respectively.

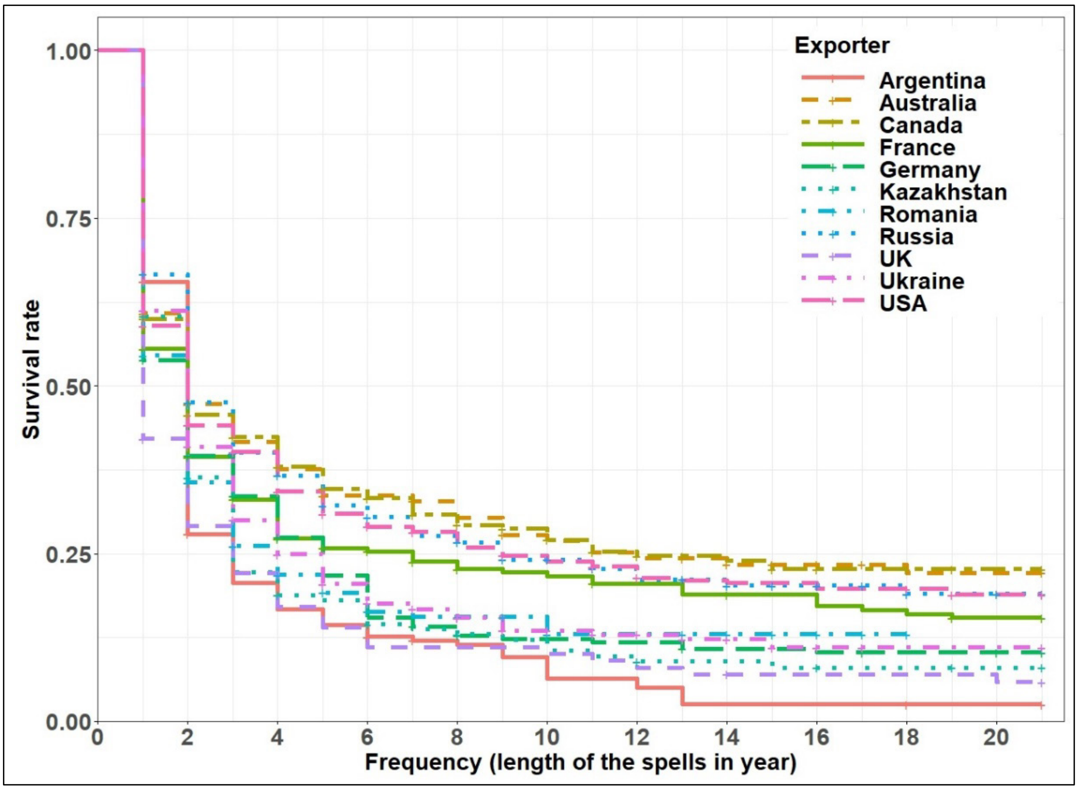

Figure 8. Kaplan-Meier survival estimator in the multiple-spells data structure

Source: study findings

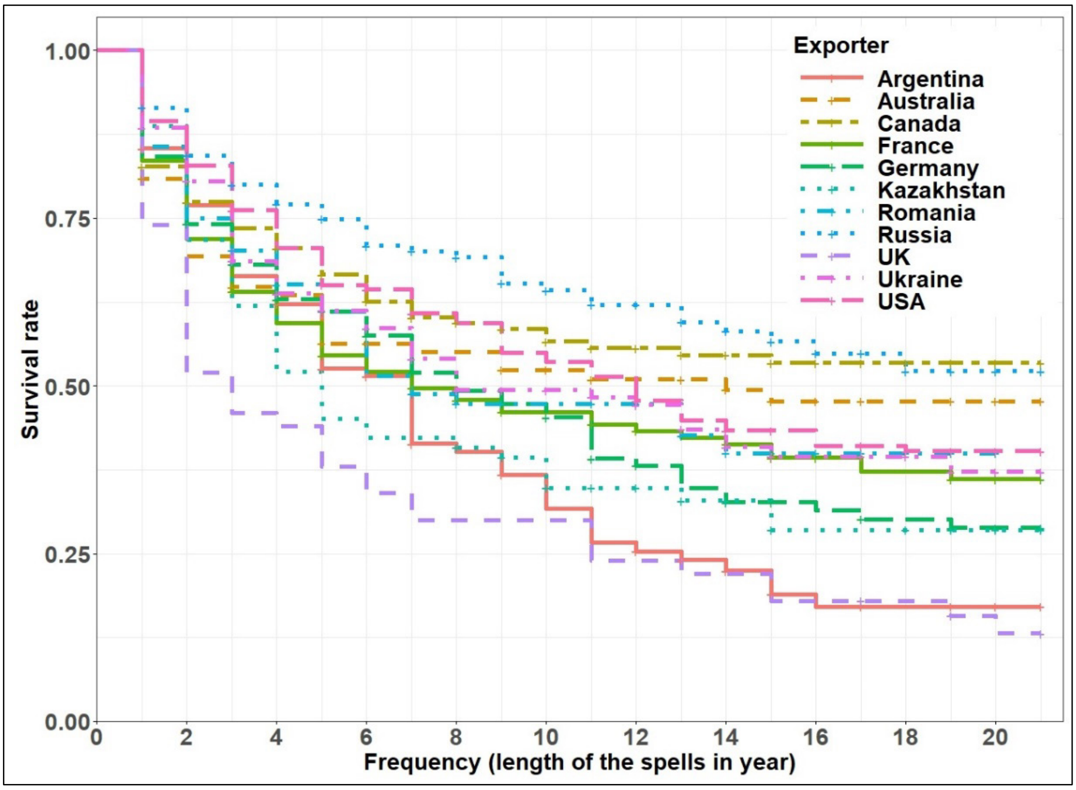

Figure 9. Kaplan-Meier survival estimator in the single-spell data structure

Source: study findings

Table 4. Survival rates of the two data structure (*multiple-spells* and *single-spell*) estimation frameworks for comparison at the spell length of 11 and 18 years using the Kaplan-Meier (KM) estimator

		Survival rate retrieved from KM estimation for spells of length 11			**Survival rate retrieved from KM estimation for spells of length 18**		
	Countries	*Multiple-spells* data	*Single-spell* data	Diff*	*Multiple-spells* data	*Single-spell* data	Diff*
Old actors	USA	0.231	0.514	-0.283	0.198	0.403	-0.205
	Canada	0.253	0.556	-0.303	0.227	0.535	-0.308
	France	0.206	0.443	-0.237	0.16	0.372	-0.212
	Australia	0.252	0.51	-0.258	0.222	0.477	-0.255
	Argentina	0.0637	0.266	-0.2023	0.0255	0.171	-0.1455
	Germany	0.118	0.392	-0.274	0.103	0.302	-0.199
	UK	0.0903	0.24	-0.1497	0.0703	0.18	-0.1097
New actors	Russia	0.228	0.621	-0.393	0.19	0.522	-0.332
	Ukraine	0.13	0.483	-0.353	0.11	0.395	-0.285
	Romania	0.13	0.474	-0.344	0.13	0.4	-0.27
	Kazakhstan	0.0973	0.348	-0.2507	0.0803	0.285	-0.2047

*Diff is *multiple-spells* data survival rate minus *single-spell* data survival rate
Source: study findings

In a nutshell, the following can be stated: firstly, with a *multiple-spells* structure, the survival rates for the Kaplan-Meier estimator are almost of the same order of magnitude as for the logit estimator. Secondly, the survival probabilities are relatively overestimated for the Kaplan-Meier estimator considering the *single-spell* in comparison to the other estimators. Thirdly, the previously mentioned patterns between the various exporting countries also apply to the Kaplan-Meier estimator with *multiple-spells*.

The findings of this article must be considered in light of some limitations. As mentioned in the introduction, stable or long-term trading relationships cannot necessarily be considered a "gold standard". Frequent changes between trading partners, i.e., unstable relations, could be a sign of a high level of adaptability and flexibility. Furthermore, as the focus of this article is on the estimation of baseline hazard and survival rates, i.e. the stability (duration) of trade relations (between nations) regardless of the extent of trade relations, considering the extent of trade relations would go beyond the aim of this study and address another (additional) question. In this regard, the quantities of trade per destination are not considered as a driver. Therefore, the results for a country with very stable trade relations with its main trading partners may be strongly influenced by some fluctuations in trade regimes with some very minor trading partners which are just above the 50-tonne threshold applied. Although this is an issue for all exporters in our dataset and all of them can be affected by that at different magnitudes, it can be analysed in the full hazard model and the quantity of trade could be one of the different covariates that are common in trade duration studies. The level of domestic wheat production of the importer could be another covariate. These are topics for future research.

6 Conclusion

This article compared trade duration differences between eleven major wheat exporters for the 2001-2021 period by using aggregated six-digit HS code wheat trade data. We addressed the research question of whether there are different survival rate clusters between newly emerging ECA wheat exporting countries (KRU and Romania) and "old" actors (the USA, Canada, Australia, Germany, France, Argentina, and the UK) and if there is a correlation between trade stability and trade partner diversification. Trade duration data was used to estimate the baseline hazard ratio of the wheat trade between each major exporter and all their importers. The estimated baseline hazard through logistic regression was employed to estimate the discrete time-to-event survival function for each exporter. Furthermore, the classical non-parametric Kaplan-Meier estimator was also employed to test the robustness of the estimated survival rates.

The results show that, primarily, we can observe a kind of duration dependence in continuing trade relations that differs between countries, and longer trade relations in the past can increase the probability of trade perpetuation. Secondly, there is no clear distinction between "new" and "old" actors in terms of the stability of trade relations. The trade survival pattern is diverse between the two groups, suggesting that factors such as the types of wheat traded, the size of the trade, the geographical position of the exporters, and unstable macroeconomic conditions might play a larger role than the length of the presence of an exporting country on the world market. Our estimation results indicate that the discrete-time hazard model within the logit estimation approach provides comparable but remarkably lower survival rates in the *single-spell* data structure compared to the *multiple-spells* data structure. Moreover, in the *multiple-spells* data structure, the discrete-time hazard model and the continuous-time Kaplan-Meier estimator generate the same numerical outputs. However, we observe that the survival rates are significantly inflated within the Kaplan-Meier estimator in the *single-spell* data structure compared to the *multiple-spells* data structure or even to the discrete-time hazard model in the *single-spell* data structure. The overestimation of the survival rates of the *single-spell* data by the Kaplan-Meier estimator and underestimation by the logit model are due to the ignoring of disruptions in the Kaplan-Meier estimator and the counting for disruptions in the logit model. This is not the case for the *multiple-spells* structure. Therefore, we can conclude that a *multiple-spells* data structure is a more robust choice across different estimators and should be preferred in further regression analyses with discrete-time hazard models or the COX proportional hazards model for the wheat market (or any other commodities markets), as it can provide more reliable baseline hazards. Moreover, we observe a positive correlation between exporters' trade stability and the diversification of trade partners, which is worthy of further research in the future with further observations and/or with firm-level data. With future research and a more mature, strengthened database, different covariates that are common in gravity types of studies could be added to each regression to find influential factors on hazard ratios. Additionally, comparative variables could be added to test the role of the intensive margin in the wheat trade. Furthermore, wheat production in importing and exporting countries will be a potential variable that can be considered.

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Data Availability Statement

The trade data used in our empirical analysis are provided at https://doi.org/10.15456/gjae.2025002.0938236463.

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Appendix

Table A1. The estimation of coefficients of the logit model with the *multiple-spells* data structure (parameter γ_t in logit model Equation 5)

	Wheat exporting countries (*multiple-spells* structure)										
	Old actors							New actors			
year	USA	Canada	France	Australia	Argentina	Germany	UK	Russia	Ukraine	Romania	Kazakhstan
γ1	-0.36** (0.12)	-0.41** (0.13)	-0.22 ° (0.13)	-0.44** (0.17)	-0.64*** (0.14)	-0.15*** (0.12)	0.32 (0.20)	-0.69*** (0.12)	-0.46*** (0.12)	-0.19 (0.14)	-0.42** (0.16)
γ2	-1.09*** (0.18)	-1.16*** (0.19)	-0.90*** (0.19)	-1.25*** (0.27)	0.30 ° (0.17)	-1.03*** (0.19)	-0.80* (0.33)	-0.91*** (0.16)	-0.70*** (0.16)	-0.65** (0.21)	-0.41° (0.21)
γ3	-2.31*** (0.32)	-2.54*** (0.37)	-1.65*** (0.28)	-2.01*** (0.40)	-1.06*** (0.29)	-1.71*** (0.28)	-1.15** (0.43)	-1.67*** (0.24)	-1.01*** (0.21)	-1.03*** (0.29)	-0.45 (0.28)
γ4	-1.76*** (0.27)	-2.15*** (0.33)	-1.55*** (0.31)	-2.24*** (0.47)	-1.41*** (0.37)	-1.50*** (0.30)	-1.22* (0.51)	-2.39*** (0.35)	-1.60*** (0.29)	-1.67*** (0.41)	-1.72*** (0.49)
γ5	-2.22*** (0.35)	-2.37*** (0.40)	-2.89*** (0.59)	-2.13*** (0.47)	-1.86*** (0.48)	-1.33*** (0.31)	-1.54* (0.64)	-1.97*** (0.32)	-1.52*** (0.32)	-2.02*** (0.53)	-3.22** (1.02)
γ6	-2.72*** (0.46)	-3.15*** (0.59)	-3.93*** (1.01)	-19.57 (1679.5)	-1.95*** (0.54)	-0.92** (0.32)	-1.30* (0.65)	-2.86*** (0.51)	-1.82*** (0.41)	-1.79*** (0.54)	-1.39** (0.5)
γ7	-3.60*** (0.72)	-2.52*** (0.47)	-2.73*** (0.6)	-3.69*** (1.01)	-3.18*** (1.02)	-2.37*** (0.60)	-18.57 (1966.65)	-2.29*** (0.43)	-3.00*** (0.73)	-3.00** (1.03)	-2.89** (1.03)
γ8	-2.40*** (0.43)	-2.96*** (0.59)	-3.07*** (0.72)	-2.49*** (0.6)	-2.89*** (1.03)	-2.23*** (0.61)	-18.57 (1966.65)	-3.35*** (0.72)	-2.49*** (0.60)	-18.57 (1458.51)	-2.83** (1.03)
γ9	-3.05*** (0.59)	-4.01*** (1.01)	-3.71*** (1.01)	-2.40*** (0.6)	-1.61* (0.63)	-3.22** (1.02)	-18.57 (1966.65)	-2.24*** (0.47)	-1.95*** (0.54)	-18.57 (1496.40)	-2.71** (1.03)
γ10	-3.38*** (0.72)	-2.77*** (0.60)	-3.69*** (1.01)	-3.43*** (1.02)	-0.69 (0.55)	-18.57 (1304.53)	-2.30* (1.05)	-18.57 (1031.32)	-17.57 (791.24)	-1.61* (0.63)	-1.87* (0.76)
γ11	-3.35*** (0.72)	-2.66*** (0.60)	-2.94*** (0.73)	-2.67*** (0.73)	-17.57 (1251.05)	-3.18** (1.02)	-2.20* (1.05)	-2.83*** (0.73)	-3.09*** (1.02)	-18.57 (1743.25)	-2.49* (1.04)
γ12	-2.57*** (0.52)	-3.69*** (1.01)	-18.57 (1072.32)	-3.33** (1.02)	-1.39 ° (0.79)	-18.57 (1331.43)	-2.08* (1.06)	-2.12*** (0.61)	-17.57 (884.63)	-18.57 (1809.05)	-2.40* (1.04)
γ13	-3.91*** (1.01)	-18.57 (1058.11)	-2.43*** (0.60)	-19.57 (2032.32)	0.00 (0.71)	-2.40** (0.74)	-1.95° (1.07)	-18.57 (1304.53)	-2.89*** (1.03)	-18.57 (1809.05)	-18.57 (2062.64)
γ14	-3.89*** (1.01)	-3.58*** (1.01)	-18.57 (1118.62)	-3.26** (1.02)	-17.57 (1978.09)	-18.57 (1423.36)	-18.57 (2465.33)	-3.09*** (1.02)	-17.57 (989.05)	-18.57 (1882.92)	-18.57 (2062.64)
γ15	-18.57 (931.81)	-2.83*** (0.73)	-18.57 (1135.45)	-19.57 (2242.37)	-17.57 (1978.09)	-18.57 (1423.36)	-18.57 (2662.86)	-18.57 (1390.63)	-2.20*** (1.05)	-18.57 (2306.1)	-2.20* (1.05)
γ16	-3.16*** (0.72)	-18.57 (1135.45)	-2.30*** (0.61)	-19.57 (2346.72)	-17.57 (1978.09)	-3.00** (1.03)	-18.57 (2662.86)	-18.57 (1423.36)	-17.57 (1398.72)	-18.57 (2917.01)	-18.57 (2174.21)
γ17	-18.57 (951.43)	-18.57 (1153.05)	-3.37*** (1.02)	-19.57 (2404.67)	-17.57 (1978.09)	-18.57 (1458.51)	-18.57 (2662.86)	-18.57 (1458.51)	-17.57 (1495.3)	-18.57 (3261.32)	-18.57 (2306.1)
γ18	-18.57 (951.43)	-18.57 (1153.05)	-3.33** (1.02)	-2.89** (1.03)	-17.57 (1978.09)	-18.57 (1496.4)	-18.57 (2662.86)	-2.71*** (1.03)	-17.57 (1615.1)	-18.57 (6522.64)	-18.57 (2306.1)
γ19	-3.09*** (0.72)	-18.57 (1190.87)	-3.30** (1.02)	-19.57 (2534.75)	-17.57 (2284.1)	-18.57 (1496.4)	-18.57 (2662.86)	-18.57 (1743.25)	-17.57 (1615.1)	-	-18.57 (2306.1)
γ20	-18.57 (994.69)	-18.57 (1211.22)	-18.57 (1279.20)	-19.57 (2534.75)	-17.57 (2284.1)	-18.57 (1496.4)	-1.61 (1.10)	-18.57 (1743.25)	-17.57 (1615.1)	-	-18.57 (2465.33)
γ21	-18.57 (994.69)	-18.57 (1211.22)	-18.57 (1279.20)	-19.57 (2534.75)	-17.57 (2284.1)	-18.57 (1537.4)	-18.57 (2917.01)	-18.57 (1809.05)	-17.57 (1615.1)	-	-18.57 (2465.33)
Obs	1680	1386	1196	800	700	1051	345	1358	1085	613	565
AIC	1091.92	897.13	879.43	540.52	796.6	943.12	349.80	1081	1100.44	618.05	576.27
Pseudo-R² (1)	0.29	0.29	0.31	0.30	0.21	0.27	0.36	0.20	0.18	0,26	0.25
Pseudo-R² (2)	0.22	0.22	0.23	0.22	0.13	0.19	0.24	0.14	0.12	0,17	0.16

AIC: Akaike information criterion. Obs: No of observations. Standard error in parenthesis ():
Pseudo-R² (1): Cragg-Uhler Pseudo-R², Pseudo-R² (2): McFadden Pseudo-R².
Significance level: "***": p<0.001; "**": p<0.01; "*": p<0.05; "°"p<0.1.
Source: study findings

Table A2. The estimation of the baseline hazard from the logit model with the *single-spell* data structure (parameter γ_t in logit model Equation 5)

	Wheat exporting countries (*single-spell*)										
	Old actors							New actors			
year	USA	Canada	France	Australia	Argentina	Germany	UK	Russia	Ukraine	Romania	Kazakhstan
$\gamma 1$	-0.87*** (0.18)	-0.44* (0.18)	-0.35° (0.18)	-0.48* (0.22)	-0.38° (0.21)	-0.03 (0.18)	0.08 (0.28)	-0.90*** (0.19)	-0.31° (0.18)	0.29 (0.22)	-0.67** (0.25)
$\gamma 2$	-1.31*** (0.21)	-0.83*** (0.21)	-0.76*** (0.21)	-0.72** (0.25)	-0.12 (0.22)	-0.51* (0.21)	-0.05 (0.33)	-0.68*** (0.19)	-0.18 (0.19)	0.11 (0.24)	-0.10 (0.25)
$\gamma 3$	-1.42*** (0.23)	-1.28*** (0.24)	-0.93*** (0.23)	-1.61*** (0.35)	-0.65** (0.25)	-0.89 (0.24)	-0.64 (0.41)	-1.11*** (0.21)	-0.51* (0.21)	-0.77** (0.27)	-0.20 (0.28)
$\gamma 4$	-1.22*** (0.23)	-1.85*** (0.30)	-1.18*** (0.26)	-1.61*** (0.37)	-0.77** (0.27)	-0.93 (0.25)	-1.04* (0.48)	-1.22*** (0.23)	-0.82*** (0.24)	-1.08*** (0.31)	-0.66* (0.32)
$\gamma 5$	-1.76*** (0.28)	-1.53*** (0.28)	-1.23*** (0.28)	-1.59*** (0.37)	-0.88** (0.29)	-1.59 (0.32)	-1.22* (0.51)	-1.42*** (0.25)	-0.92*** (0.25)	-1.34*** (0.36)	-1.29** (0.40)
$\gamma 6$	-1.80*** (0.30)	-2.12*** (0.35)	-2.15*** (0.40)	-2.64*** (0.60)	-0.79* (0.31)	-1.54 (0.32)	-1.32* (0.56)	-2.03*** (0.32)	-1.28*** (0.29)	-1.01** (0.34)	-1.47** (0.45)
$\gamma 7$	-2.47*** (0.39)	-2.17*** (0.37)	-1.81*** (0.36)	-2.28*** (0.53)	-0.63* (0.31)	-1.55 (0.33)	-1.18* (0.57)	-1.99*** (0.34)	-1.47*** (0.32)	-1.67*** (0.45)	-1.61** (0.49)
$\gamma 8$	-2.00*** (0.34)	-2.24*** (0.40)	-2.12*** (0.43)	-3.00*** (0.73)	-1.42*** (0.42)	-1.53 (0.35)	-2.64* (1.04)	-2.50*** (0.43)	-1.24*** (0.32)	-2.30*** (0.61)	-2.20*** (0.61)
$\gamma 9$	-1.76*** (0.31)	-3.48*** (0.72)	-3.24*** (0.72)	-2.25*** (0.53)	-1.39** (0.42)	-1.54 (0.37)	-1.39* (0.65)	-1.93*** (0.36)	-2.02*** (0.44)	-18.57 (1232.66)	-1.10* (0.44)
$\gamma 10$	-2.14*** (0.37)	-1.91*** (0.38)	-2.75*** (0.60)	-2.89*** (0.73)	-0.80* (0.40)	-1.95 (0.44)	-1.87* (0.76)	-1.95*** (0.38)	-2.75*** (0.60)	-3.09** (1.02)	-1.00* (0.44)
$\gamma 11$	-2.11*** (0.37)	-2.60*** (0.52)	-2.75*** (0.60)	-2.43*** (0.60)	-0.94* (0.45)	-1.10 (0.35)	-0.69 (0.55)	-1.85*** (0.38)	-2.38*** (0.52)	-1.90** (0.62)	-1.85** (0.62)
$\gamma 12$	-1.70*** (0.33)	-2.30*** (0.47)	-2.35*** (0.52)	-3.50*** (1.02)	-0.92° (0.48)	-2.86 (0.73)	-1.61* (0.78)	-2.24*** (0.47)	-2.59*** (0.60)	-3.00** (1.03)	-2.20** (0.75)
$\gamma 13$	-1.96*** (0.38)	-3.26*** (0.72)	-2.62*** (0.60)	-18.57 (1118.62)	-0.77 (0.49)	-1.79 (0.48)	-1.10° (0.67)	-2.71*** (0.60)	-1.52*** (0.42)	-2.20** (0.75)	-1.25* (0.57)
$\gamma 14$	-2.66*** (0.52)	-3.89*** (1.01)	-3.74*** (1.01)	-3.47*** (1.02)	-1.87* (0.76)	-2.27*** (0.61)	-1.50° (0.78)	-3.76*** (1.01)	-2.30*** (0.61)	-2.71** (1.03)	-2.71** (1.03)
$\gamma 15$	-3.33*** (0.72)	-2.71*** (0.60)	-2.23*** (0.53)	-2.60*** (0.73)	-1.20° (0.66)	-17.57 (761.37)	-1.50° (0.78)	-2.92*** (0.73)	-2.60*** (0.73)	-18.57 (1743.25)	-1.39* (0.65)
$\gamma 16$	-2.58*** (0.52)	-18.57 (961.71)	-2.14*** (0.53)	-18.57 (1304.53)	-2.20* (1.05)	-2.04*** (0.61)	-17.57 (1318.73)	-3.40*** (1.02)	-17.57 (824.92)	-18.57 (1966.65)	-17.57 (1142.05)
$\gamma 17$	-3.97*** (1.01)	-3.71*** (1.01)	-2.11*** (0.53)	-18.57 (1360.06)	-16.57 (799.85)	-2.44*** (0.74)	-17.57 (1318.73)	-3.22 (1.02)	-17.57 (824.92)	-18.57 (2465.33)	-17.57 (1142.05)
$\gamma 18$	-3.93*** (1.01)	-18.57 (1018.67)	-3.53*** (1.02)	-3.05** (1.02)	-16.57 (906.94)	-17.57 (824.92)	-1.95° (1.07)	-2.94** (1.03)	-17.57 (884.63)	-18.57 (2662.86)	-2.40* (1.04)
$\gamma 19$	-3.18*** (0.72)	-18.57 (1087.11)	-2.80*** (0.73)	-18.57 (1390.63)	-16.57 (906.94)	-3.09** (1.02)	-1.95° (1.07)	-16.57 (581.98)	-2.77** (1.03)	-18.57 (3261.32)	-17.57 (1192.83)
$\gamma 20$	-17.57 (571.03)	-18.57 (1118.62)	-17.57 (747.65)	-18.57 (1458.51)	-16.57 (979.61)	-17.57 (907.61)	-1.61 (1.10)	-16.57 (619.56)	-17.57 (1398.72)	-18.57 (4612.20)	-17.57 (1398.72)
$\gamma 21$	-17.57 (603.31)	-18.57 (1211.22)	-17.57 (775.87)	-18.57 (1537.40)	-16.57 (1385.38)	-17.57 (932.48)	-17.57 (1769.26)	-16.57 (665.51)	-17.57 (1615.10)	-	-17.57 (1495.30)
Obs	1680	1386	1196	833	700	1051	345	1358	1085	613	565
AIC	1269.97	961.95	985.06	568.37	862.7	1015.49	400	1254.17	1087.56	604.60	694.59
Pseudo-R^2 (1)	0.12	0.22	0.19	0.24	0.09	0.18	0.19	0.13	0.20	0.29	0.19
Pseudo-R^2 (2)	0.08	0.16	0.13	0.18	0.05	0.12	0.12	0.09	0.13	0.20	0.12

AIC: Akaike information criterion. Obs: No of observations. Standard error in parenthesis ():
Pseudo-R^2 (1): Cragg-Uhler Pseudo-R^2, Pseudo-R^2 (2): McFadden Pseudo-R^2.
Significance level: "***": p<0.001; "**": p<0.01; "*": p<0.05; "°"p<0.1.
Source: study findings