Beyond the ban – shedding light on smallholders' price vulnerability in Indonesia's palm oil industry

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Abstract

The Indonesian government imposed an export ban on palm oil in response to soaring cooking oil prices in spring of 2022. This study aims to explore the vulnerability of smallholder farmers to this particular policy intervention within the palm oil industry. We utilise primary data to investigate smallholders' perception of the export ban and its consequences on their economic well-being using descriptive statistics and the machine learning technique Lasso. Our findings reveal that the export ban had a substantial adverse impact on smallholders, leading to increased financial strain and instability in their agricultural practices. Small-scale producers struggled to cope with the changing market dynamics, while limited access to resources further exacerbated their vulnerability. However, the households' dependence on palm oil, the farms' certification status, and various socioeconomic variables affect the extent to which smallholder farmers are impacted. This study underscores the importance of considering smallholders' vulnerability when implementing trade policy measures within the palm oil industry. Our findings are relevant to industry stakeholders as well as policymakers.

Keywords: Export Ban, Indonesia, Palm Oil, Smallholder Farmers, Trade Policy
JEL Code: Q17, Q18, O13

1 Introduction

On April 28, 2022, the Indonesian government implemented an unprecedented measure by imposing an export ban on palm oil. This step followed weeks of soaring cooking oil prices, which caused protests in the nation's capital (Llewellyn, 2022). As demonstrated by previous research, escalating food prices have been associated with social unrest (Bellemare, 2015), thereby emphasising the potential impact on political stability in Indonesia. In response to these concerns, the government's decision to enforce the export ban aimed at addressing the challenges posed by the cooking oil crisis and its potential ramifications on the well-being of the population as well as national security. Before the ban, cooking oil prices per litre surged from approximately 14,000 Indonesian Rupiah (IDR) to over 22,000 IDR[1] (Medina, 2022), disproportionately impacting the most vulnerable segments of the population. While Indonesia and Malaysia collectively produce 90% of the global palm oil supply (Qaim et al., 2020), labor shortages in Malaysia have curbed the global palm oil supply, as emphasized by anecdotal newspaper evidence (Llewellyn, 2022) and thereby contributed to increasing palm oil prices. While global food prices were already under pressure following Russia's invasion to Ukraine (von Cramon-Taubadel, 2022; Ihle et al., 2022), global prices for vegetable oils further climbed following Indonesia's export ban (see Figure 1). Additionally, due to palm oil's wide usage in household items such as shampoo, soap and processed food (Corley & Tinker, 2008), the price increase was reflected across the product aisle and increased pressure on households. Indeed, consumers have been shown to carry the biggest burden of volatile food prices (Djuric & Götz, 2016). The export ban was lifted almost one month later, after oil palm farmers protested across the country against the export ban, which adversely impacted their incomes (The Diplomat, 2022).

While the Indonesian government had previously implemented various measures, including a domestic market obligation to maintain affordable cooking oil prices (see Figure 1 for additional policies), these efforts did not achieve their intended outcomes (Llewellyn, 2022), as the rising palm oil stock market price indicates. Consequently, the government resorted to a complete ban on exports to gain control over cooking oil prices. Even though the ban was intended to stabilise cooking oil prices, benefiting the entire Indonesian population as consumers, adverse effects for palm oil producers could be expected. Of particular interest within the industry are smallholder producers, who contribute approximately 50% to the global palm oil supply (Byerlee et al., 2017). Smallholders are uniquely affected in a two-folded way: As consumers, they struggle with rising cooking oil prices, while as producers, they experience volatile farm gate prices. Smallholder households often depend solely on income from oil palm cultivation, and as small-scale farmers typically face cash constraints, they are particularly vulnerable to price fluctuations (Brandi et al., 2015; Glasbergen, 2018).

Despite contributing around 40% of the nation's total palm oil supply in Indonesia (Ruml et al., 2022), smallholders have limited involvement in the post-harvest processing, which is primarily managed by a nucleus estate of industrial producers (Watts et al., 2021). As a result, they are more susceptible to price fluctuations determined by the processing mill and have little to no bargaining power (McCarthy & Cramb, 2009). Furthermore, research conducted by Warr & Yusuf (2014) and Yamauchi & Dewina (2012) stresses the adverse impacts of rurality on consumers' vulnerability to

[1] 14,000 Indonesian Rupiah (IDR) is equal to 0.96 USD, and 22,000 IDR is equal to 1.52 USD using the exchange rate from April 19, 2022.

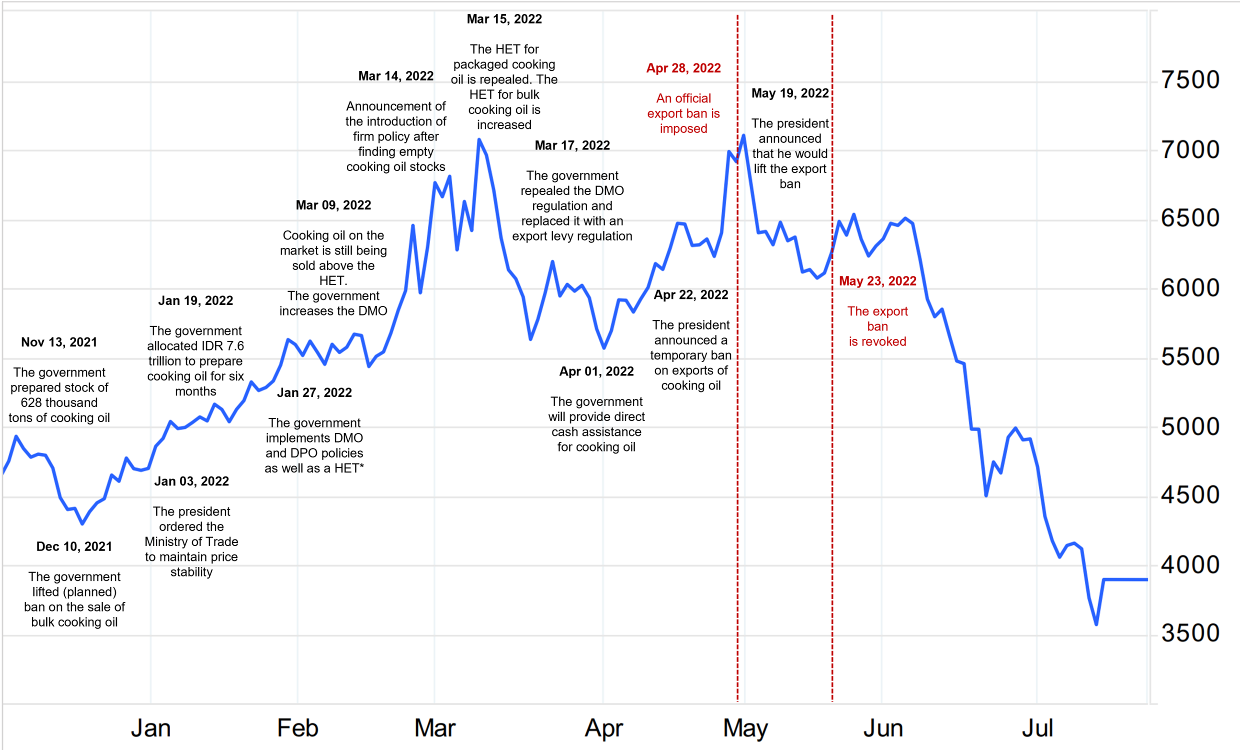

Figure 1: *Timeline of export ban and palm oil world market price (Dec 2021 – Jul 2022, in Malaysian ringgit per ton).*
Source: Own illustration.

food prices. As oil palm smallholders typically operate in rural contexts, the spatial component adds to their vulnerability and potentially makes mitigating shocks more difficult (Sibhatu et al., 2022). The heightened intensity of price shocks on rural households is also underscored in studies conducted by Harttgen et al. (2016) and Rudolf (2019), who utilise panel data to investigate the impact of maize price shocks on households' food security. The authors reveal that increased maize prices led to a considerable 12.6% reduction in calorie intakes for rural households, rendering them the most vulnerable group to food insecurity following a price shock. Additionally, evidence suggests that export bans can exacerbate price volatility instead of stabilising prices (Porteous, 2017). Smallholders may experience some benefits from global price increases but the overall welfare effect has been shown to be modest (Nakelse et al., 2018). Research has demonstrated that oil palm expansion contributes to food security for rural households (Tabe-Ojong Jr et al., 2023), improved household welfare (Mehraban et al., 2021), and enhanced nutrition among rural households (Chrisendo et al., 2022), thereby fostering rural development (Qaim et al., 2020). Nonetheless, it is essential to recognize that these gains may also interact with the price volatility previously outlined (Porteous, 2017), warranting careful consideration in policy formulations surrounding the palm oil industry. Furthermore, adverse impacts of volatile food prices on households' nutrition are further amplified when the household head is female (Kumar & Quisumbing, 2013). Similarly, Block et al. (2004) find comparable results for female-headed households during the 1997/1998 drought and financial crisis in Indonesia. This becomes especially pertinent considering the male-dominated nature of oil palm cultivation in Indonesia (Mehraban et al., 2022).

Against this background, the objective of our paper is to assess the resilience of oil palm cultivating rural households to volatile market prices, particularly in light of the export ban's impact. Using primary data collected in the Indonesian province Jambi, we aim to explore how smallholders navigate the dual roles of being both producers and consumers amidst market disruptions. To achieve this, we measure the export ban's influence on farmers' livelihoods by examining reported price differences for fresh fruit bunches before and after the ban, focusing on farm gate prices received by smallholders upon harvest per kilogram of fresh fruit bunch. Our investigation encompasses a range of descriptive variables, shedding light on smallholders' perceptions of the ban and their coping mechanisms, including potential adjustments in food consumption patterns. Additionally, through empirical analysis employing machine learning (ML), we aim to discern the differential impact of the export ban on various groups of smallholders, with a particular emphasis on identifying farm characteristics that may render some smallholders more vulnerable to adverse effects following the ban. By delving into these aspects, our study seeks to address two key questions: Firstly, what is smallholders' perception of the export ban, and secondly, are there differences in smallholders' vulnerability to price fluctuations with varying levels of endowments or access to resources? Ultimately, our research aims to provide valuable insights for policymakers, and industry stakeholders informing future strategies to enhance the well-being of those involved in the palm oil industry.

To the best of our knowledge, this study represents the first investigation into the effects of the Indonesian palm oil export ban on smallholders' livelihoods, encompassing the trade-off between small-scale producers and consumers. Our research yields novel and important insights, as it addresses the extensive discourse surrounding the palm oil industry and its vulnerability to diverse policy regulations. As sustainability and market dynamics remain focal points of discussion within the palm oil sector, our findings hold relevance for industry stakeholders and policy-makers alike. By highlighting the trade-offs that impact the well-being of smallholders, our study underscores the importance of carefully considering the implications when crafting policies that affect this essential sector.

The remainder of our paper is structured as follows. Section 2 introduces the data, Section 3 presents the methodology. In Section 4 we present our results and discuss them. Section 5 focuses on concluding remarks.

2 Data

Our study uses primary data, which was collected from October 2022 until February 2023 in the province of Jambi, Indonesia (see Figure 2). The study was approved by the ethical commission of the Indonesian government. Jambi renders the ideal background for this study, as 40% of oil palm plantations in this region are managed by smallholders (Apriani et al., 2020; Euler et al., 2016). Furthermore, livelihoods rely heavily on oil palm cultivation (Qaim et al., 2020), which has contributed to a considerable reduction in the national poverty line (Gatto et al., 2017).

We built our sample by firstly identifying the biggest oil palm cultivating regencies within Jambi province (Krishna et al., 2017). Following that, we randomly selected two regencies. Furthermore, four districts were randomly selected per regency. Within the districts, we randomly selected two villages per district. As we were interested in possible differences between non-certified and certified smallholders, we purposely added villages with certified smallholders to our sample. In each village, farmers were randomly approached by a team of trained, local enumerators. Wherever possible, not more than two farmers were interviewed per street, to control for neighbouring effects. Farmers were interviewed individually, as asking about opinions on political topics, such as the export ban, can be considered a sensitive topic. Only smallholder farmers cultivating less than 20 hectares of oil palm plantations and those who are primarily cultivating oil palms were admitted to participate in the study. Participation was completely voluntary and could be withdrawn at any point throughout the interview. The overall sample consists of 383 smallholders. The sample size is based on a power calculation and the sample is further described in section 4.1.

Figure 2: *Map of the Indonesian provinces, Jambi province in grey.*
Source: Own illustration.

3 Estimation strategy

In the first part (Section 3.1), we introduce the ML method least absolute shrinkage and selection operator (Lasso) for feature selection. In the second part (Section 3.2), we present the post-Lasso ordinary least squares (OLS).

3.1 Lasso for feature selection

Agricultural prices are linked to a large set of determinants (Meyer & Yu, 2013; Tadasse et al., 2016). However, not all determinants carry the same importance. In cases with high-dimensionality, the ML technique Lasso is an efficient and suitable method for feature selection (Tibshirani, 1996). Lasso is a regularised regression method, penalising the absolute size of coefficient estimates. Lasso is an approximate sparse method, implying that among a number of regressors of a specific model, only some regressors are relevant to capture the features of a specific regression, meaning that only certain covariates have a stimulating effect on the outcome. In other words, Lasso is useful when many potential covariates exist but it is of interest to include only the covariates with a stimulating effect (Belloni & Chernozhukov, 2013; Tibshirani, 1996). Lasso aims to minimise the sum of the squared residuals as well as the penalty term lambda (λ) that penalises the size of the model through the sum of absolute values of the coefficients. This can be defined as:

$$\arg\min_{\beta} N \sum_{i=1} (Y_i - \beta X_i)^2 + \lambda(\|\beta\|_q)^{1/q} \quad (1)$$

where $\|\beta\|_q$ is defined as:

$$\|\beta\|_q = \sum_{k=1}^{K} |\beta_k|^q \quad (2)$$

For q = 1, this corresponds to Lasso, while for q = 2 the equation highlights a ridge regression (Athey & Imbens, 2019). The penalty term λ, that Lasso aims to minimise next to the sum of the squared residuals, ranges between 0 and 1. Due to the lowering process coefficients with relatively little explanatory power decrease to zero. Through this lowering process, only the most important features are included in the model.

λ is commonly chosen by cross-validation (cv) (Belloni et al., 2014; Athey & Imbens, 2019). To increase robustness of the feature selection results, we determine λ with the minimum of the Bayesian information criterion (minBIC) and an adaptive Lasso (adaptive) additionally. In summary, different Lasso models are estimated and compared, leading to different values for λ and thus to different features.

Storm et al. (2020) emphasise that ML methods can overcome many limitations of econometric models. Lasso has been applied for feature selection in predicting irrigation investments for small-scale Nicaraguan farmers (Mullally & Chakravarty, 2018), the prediction of subjective poverty in China (Maruejols et al., 2023), the analysis of energy consumption in Vietnam (Maruejols et al., 2022), to predict access to healthful food retailers in the US (Amin et al., 2021), and to search for predictors of food insecurity in Malawi (Knippenberg et al., 2019).

Belloni & Chernozhukov (2013) demonstrate that the OLS post-Lasso estimation performs at least as effectively as Lasso in terms of convergence rate. Additionally, it has the advantage of a smaller regularization bias. Moreover, the performance of the post-Lasso OLS remains consistent even if the Lasso-based model selection overlooks certain components of the "true" best s-dimensional approximation within the nonparametric regression model. The OLS post-Lasso estimator outperforms Lasso by achieving a noticeably faster convergence rate. Therefore, a post-model estimator that applies an OLS to the model selected by the different Lasso algorithms (cv, minBIC, and adaptive) is applied. The data-driven variable selection avoids multicollinearity and an overfitting of the model. An example for multicollinearity could be for instance regarding farmer's access to credit and farmer's education. Afterward, we estimate an OLS model using the selected regressors identified by the different Lasso algorithms (cv, minBIC, and adaptive). Using Lasso mitigates p-hacking concerns because the approach ensures a well-founded variable selection. Table 1 presents all 32 variables ($\beta_1, \ldots, \beta_{32}$) that are included in the Lasso feature selection process.

3.2 OLS for post-Lasso regression

As discussed in the first part of the section (Section 3.1), we estimate an OLS regression with clustered standard errors on the district level. We use the variables selected by the different Lasso algorithms (cv, minBIC, and adaptive) as regressands. An OLS regression model is typically used to model the relationship between a continuous dependent variable and one or more independent variables Angrist & Pischke (2009). We estimate the following form:

$$Y_i = \beta_0 + \beta_1 c_i + \delta_b + \epsilon_i \tag{3}$$

where Y_i is the price difference in the month before and in the month after the implementation of the export ban for individual i, c_i is a vector containing the variables selected based on the different Lasso algorithms for individual i. ϵ_i is the independently and identically distributed error term with a mean of zero and a variance of σ_e^2. We use district specific δ_b fixed effects. The fixed-effects control for differences in the levels of variables associated with districts in each province. Such unobserved region-specific and time-invariant heterogeneity can be for example geography or the proportion of arable land. The analysis is conducted by using Stata 18 and the program lassopack, introduced by Ahrens et al. (2020).

Endogeneity arises when one or more of the independent variables are correlated with the error term ϵ_i. Potential sources of endogeneity include omitted variables bias. In our case, this would mean that the dependent variable and the regressors may be biased because other unobserved factors influencing prices are not included in the model. Reverse causality (meaning that the export ban itself could be influenced by factors related to price differences) and simultaneity concerns (in cases where there is a feedback loop between the dependent variable and one or more of the regressors) might be additional sources of endogeneity. However, as our dependent variable is the price difference due to an exogenous shock, the unannounced export ban which was implemented by the Indonesian Government, and our regression only considers farmers' characteristics, it is unlikely that we face reverse causality and simultaneity concerns.

4 Results and Discussion

4.1 Descriptive statistics

Table 1 shows the summary statistics of the sampled farmers. The average respondent is 49 years old. The majority of farmers are male (82.5%), which corresponds to the male-dominated character of oil palm cultivation (Mehraban et al., 2022). The majority of farmers are married (92.1%). A share of 84.1% stated that they or their parents were part of the transmigration program, which relocated people from the main islands to the Indonesian periphery in an effort to foster development through farming (Fearnside, 1997). On average, farmers reported 10 years of schooling, indicating a slightly higher value than the national average of 8 years (Our world in data, 2023). This translates in detail to more than 15% of respondents who went to university, 33.9% completed high school and 21.9% completed middle school. 61.4% of the farmers have access to credit and 82.8% have a bank account, hinting at farmers' financial inclusion. Focusing on the household characteristics, the average household size is four, while the average number of income generating people is close to two. 64.2% stated that oil palm cultivation is their primary income source, while for 16.4% off-farm palm cultivation labour is the primary income source. Regarding the plantation characteristics of respondents, it is noteworthy that 40.8% are not operating under any certificate, which aligns with previous findings indicating considerable challenges faced by farmers when adopting such certifications (Watts et al., 2021). The low adoption rate is evident in the sample, with only 3.4% of respondents reporting that their plantations are fully certified.

Among those with certified plantations, a larger proportion holds RSPO (roundtable of sustainable palm oil) certification as opposed to ISPO (Indonesian sustainable palm oil) certification (Astari & Lovett, 2019). 16.4% of the farmer in our sample are part of a cooperative and the average farm size is 3.3 hectare, which corresponds to the median farm size as of 2018 (Chrisendo et al., 2021). The majority of respondents (66.8%) indicate that they sell their fresh fruit bunch harvest to middlemen, while only 14.1% opt to sell directly to a mill. Sales through middlemen are often preferred as they offer immediate payment, whereas selling to mills through cooperatives, often involves delays in payment. However, it is worth noting that prices for sales to middlemen are typically lower compared to mill prices (Lee et al., 2014), which further hints at the cash constraint challenges faced by small-scale farmers (Glasbergen, 2018). Figure 3 shows the boxplot for the price difference before and after the shock. Three farmers stated that they received a higher price in comparison to the period before the export ban. The remaining sample (99.5%) faced a negative price shock.

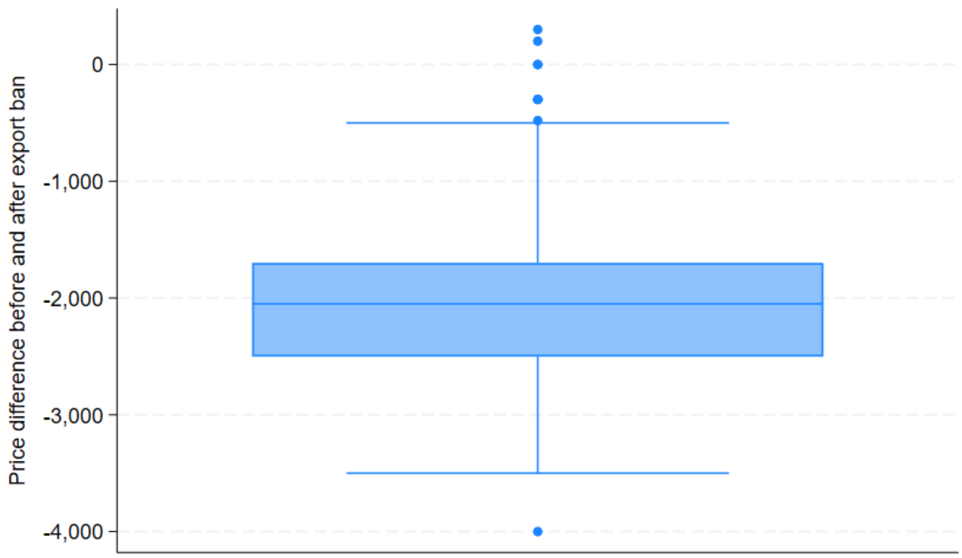

Figure 3: *Boxplot of the price difference for fresh fruit bunches one month before and one month after the export ban (in IDR, N=383).*
Source: Own illustration.

4.2 Smallholders' opinion on the palm oil export ban

Table 2 shows the results of farmers' opinion on the palm oil export ban. The majority of smallholders state they did not regard the governments' export ban as a good idea (85.4%), with only 9.9% of respondents in our sample considering the introduction of the export ban a good idea. Furthermore, 62.1% of smallholders' associate higher household expenses with the ban, while 98.7% state they associate lower farm profits with the export ban. This is underlined by 97.9% of farmers stating they perceive prices for fresh fruit bunches lower than usual during the export ban. Only 1.6% of farmers did not recognise a change for prices of fresh fruit bunches (FFB) during the export ban. Additionally, 16.2% of farmers did not experience any changes in household expenses, while 21.7% of farmers in our sample even experienced lower household expenses associated with the

Table 1: Summary statistic - farmer and household characteristics.

	Unit	Mean	SD	Min.	Max.
Outcome of interest					
Price difference before and after export ban	in IDR	-2,030.789	645.239	-4,000.000	300.000
Farmer's characteristics					
Farmer's age	in years	48.893	98.801	20.000	1,965.000
Farmer's age (sqr.)	in years (sqr.)	12,126.731	197,197.180	400.000	3,861,225.000
Farmers' gender	0=male, 1=female	0.175	0.380	0.000	1.000
Dummy if farmer is married	0=no, 1=yes	0.921	-	0.000	1.000
Dummy if farmer is widowed	0=no, 1=yes	0.031	-	0.000	1.000
Dummy if farmer or farmers parents are trans migrants	0=no, 1=yes	0.841	-	0.000	1.000
Farmer's years of education	in years	10.170	3.899	0.000	20.000
Dummy if farmer has university experience	0=no, 1=yes	0.157	-	0.000	1.000
Dummy if farmer has primary education or less	0=no, 1=yes	0.285	-	0.000	1.000
Dummy if farmer has completed middle school	0=no, 1=yes	0.219	-	1.000	1.000
Dummy if farmer has completed high school	0=no, 1=yes	0.339	-	1.000	1.000
Dummy if farmer has access to credit	0=no, 1=yes	0.614	-	0.000	1.000
Dummy if farmer has a bank account	0=no, 1=yes	0.828	-	0.000	1.000
HH's characteristics					
Farmer's HH size	continuous variable	4.052	1.387	1.000	9.000
Number of people in HH that generate income	continuous variable	1.718	0.795	1.000	5.000
Farmer' household income	in IDR	4.363	2.287	1.000	9.000
Farmer's monthly average income from oil palm	in IDR	2.995	2.124	1.000	9.000
Farmer's monthly average income outside oil palm	in IDR	0.493	0.853	0.000	9.000
Household's income outside farming	in IDR	1.945	1.932	0.000	9.000
HH income, per capita	in IDR	1.207	0.815	0.167	5.000
Dummy if primary income source is oil palm cultivation	0=no, 1=yes	0.642	-	0.000	1.000
Dummy if primary income source is off-farm labour	0=no, 1=yes	0.164	-	0.000	1.000

Table 1: Summary statistic - continued

	Unit	Mean	SD	Min.	Max.
Farm management characteristics					
Dummy if farmer has no plantation certified	0=no, 1=yes	0.408	-	0.000	1.000
Dummy if farmer has partly plantation certified	0=no, 1=yes	0.558	-	0.000	1.000
Dummy if farmer has all plantation certified	0=no, 1=yes	0.034	-	0.000	1.000
Dummy if farmer has any RSPO plantation certified	0=no, 1=yes	0.560	-	0.000	1.000
Dummy if farmer has any ISPO plantation certified	0=no, 1=yes	0.031	-	0.000	1.000
Dummy if farmer is part of an oil palm farmer group	0=no, 1=yes	0.266	-	0.000	1.000
Dummy if farmer is part of a cooperative	0=no, 1=yes	0.164	-	0.000	1.000
Farmer's total area of oil palm plantation	in ha	3.363	2.899	0.250	20.000
Dummy if farmer sell FFBs to middleman	0=no, 1=yes	0.668	-	0.000	1.000
Dummy if farmer sell FFBs to mill	0=no, 1=yes	0.141	-	0.000	1.000
N	383				

Source: Own illustration.

trade policy.

When asked on how smallholders' think the price for fresh fruit bunches is determined, 33.7% state the Indonesian government, followed by the mill (23.0%). 22.5% think the market determines the price, 23.0% answered the mill determines the FFB prices and more than 17.8% of farmers in our sample stated they do not know how the price for fresh fruit bunches is determined, which is surprisingly large (compare Figure 4). It is noteworthy that the majority of respondents believe that the Indonesian government plays a considerable role in determining fresh fruit bunch prices. This perception suggests that smallholders associate substantial influence with the Indonesian Government within the palm oil industry, possibly influenced by governmental interventions like the export ban. This also reflects the expectations that smallholders may have regarding the Indonesian Government's market power within the palm oil industry. Notably, this finding aligns with recent declines in approval ratings (Llewellyn, 2022).

62.7% of smallholders recognised changes in prices for cooking oil in the months prior to the export ban. However, following the export ban, 54.8% did not perceive cooking oil as cheaper, while 41.8% state cooking oil prices sank following the ban. In addition, it is noteworthy that 58.2% of farmers acknowledged the positive effect of cheaper prices for cooking oil, which they believed outweighed the price decline for fresh fruit bunches. This underscores the duality of smallholders in this context, where they are producing palm oil and experienced a price decline following the export ban, while also recognizing the benefits of more affordable cooking oil. 62.7% state they did not make changes in their usual consumption patterns following the export ban, which hints at a certain level of resilience among smallholders, despite price dynamics.

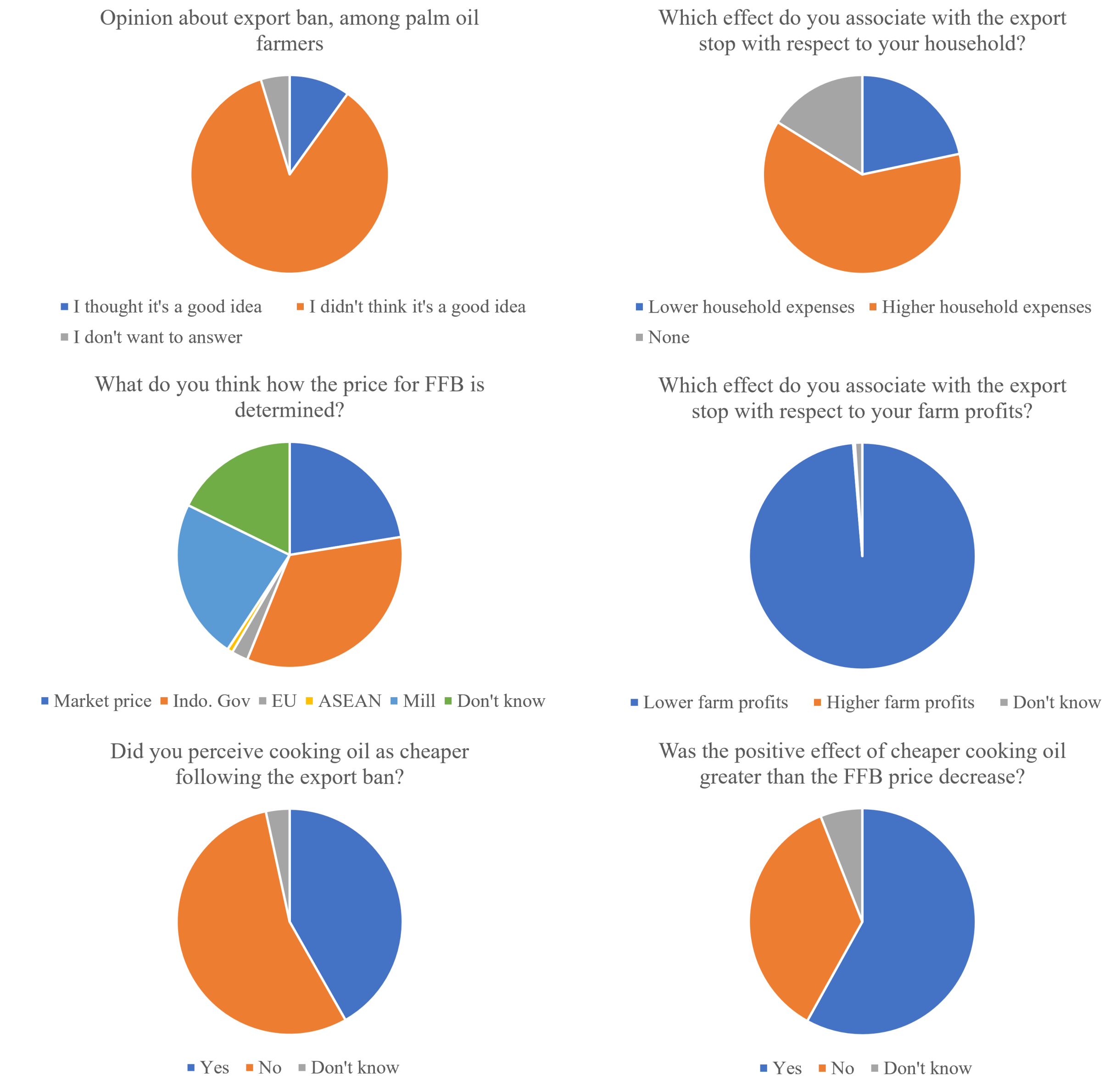

Figure 4: *Farmer's opinion on the palm oil ban (N=382). Source: Own illustration.*

Table 2: Summary statistic - farmer's opinion on the palm oil ban.

	Freq.	Percent
What did you think about the export ban imposed by the Indonesian government?		
I thought it's a good idea.	38	9.92
I didn't think it's a good idea.	327	85.38
I don't want to answer.	18	4.70
Which effect do you associate with the export stop with respect to your household expenses?		
Lower household expenses.	83	21.67
Higher household expenses.	238	62.14
None of the above.	62	16.19
Which effect do you associate with the export stop with respect to your farm profits?		
Lower farm profits.	378	98.69
Higher farm profits.	1	0.26
None of the above.	4	1.04
How did you perceive the price for FFB during the export ban?		
Lower than usual.	375	97.91
Normal, I didn't recognise big changes.	6	1.57
I don't know.	2	0.52
What do you think how the price for FFB is determined?		
Market price	86	22.45
Indonesian Government	129	33.68
European Union	9	2.35
ASEAN	3	0.78
The Mill	88	22.98
I don't know.	68	17.75
Did you recognise changes in price for cooking oil during the months of March and April, before the export ban was implemented?		
Yes.	240	62.66
No.	92	24.02
I don't want to answer.	51	13.32
Did you perceive cooking oil as cheaper following the export ban?		
Yes.	160	41.78
No.	210	54.83
I don't want to answer.	13	3.39
Would you say the positive effect of cheaper prices for cooking oil was bigger than the price decrease for FFB?		
Yes.	223	58.22
No.	138	36.03
I don't know.	17	4.44
I don't want to answer.	5	1.31
Did your household make changes regarding the food you usually eat due to the price volatility for FFB?		
Yes, consumed more of cheap foods.	142	37.08
No.	240	62.66
I don't want to answer.	1	0.26
N	383	

Source: Own illustration.

Table 3: Lasso selection (N=383)

	cv	minBIC	adaptive
Dummy if primary income source is off-farm labour	x	x	x
Dummy if farmer has a bank account	x	x	x
Farmers' gender	x		x
Farmer's household size	x		x
Dummy if primary income source is oil palm cultivation	x		x
Farmer's monthly average income from oil palm	x		x
Dummy if farmer has all plantation certified	x		x
Farmer's age	x		x
Dummy if farmer has any ISPO plantation certified	x		x
Dummy if farmer has partly plantation certified	x		
Dummy if farmer or farmers parents are trans migrants	x		
MSE	305,637	338,569	306,806
R^2	0.19	0.10	0.19

cv refers to cross-validation, minBIC to minimum of the Bayesian information criterion, and (adaptive) to an adaptive Lasso.
Source: Own illustration.

4.3 Post-Lasso estimates

As mentioned in Section 3.1, we apply and compare three different approaches on how to select λ (cv, minBIC, and adaptive Lasso). The three different Lasso models lead to different values for λ and therefore also to different feature selections. The selection of a variable across various Lasso approaches suggests its importance in influencing the outcome of interest, which, in our case, is the price difference for fresh fruit bunches before and after the export ban. Table 3 shows the variables that are selected for each of the three techniques. Only two variables have been selected across the three different approaches, highlighting the importance of these two independent variables on the dependent variable. These are a dummy indicating whether the primary income source is off-farm labour, and a dummy whether a farmer has a bank account. The selected variables vary in dependency of the selected selection method. The most variables have been selected by cv Lasso (11) and only 2 variables have been selected by minBIC Lasso.

A post-Lasso OLS is applied to the different models selected by the three Lasso algorithms. The results are presented in Table 4. Column (1) presents the results without and column (2) presents the results including regional fixed effects for Lasso based on cv. For respondents whose primary income source is off-farm labour, making oil palm cultivation their secondary income, the impact of the export ban is more pronounced, resulting in larger price differences (the price one month before and one month after the introduction export ban) compared to those whose primary income source is oil palm cultivation. We argue that individuals with oil palm cultivation as their primary income source may benefit from higher levels of experience, specialisation, economies of scale, and stronger connections within farmer networks. These factors potentially contribute to better price cushioning mechanisms, such as information sharing, which could explain the observed smaller price differences following the export ban (Lee et al., 2014). Furthermore, being a female farmer is positively associated with the price difference, meaning female farmers are more likely to face larger price changes for fresh fruit bunches following the ban compared to their male counterparts. This finding aligns with our initial expectation, given the male-dominated nature of the palm oil industry

(Mehraban et al., 2022). This gender disparity may influence female farmers' negotiating position and access to support networks, thereby increasing their vulnerability to market risks. Notably, farmers with a transmigration background also exhibit a positive association with experiencing larger price differences after the export ban. This observation can be linked to the earlier-discussed point that transmigration smallholders are closely integrated into the structural development of agriculture in Indonesia's rural regions (Lee et al., 2014). Consequently, their farm management is closely tied to industrial producers (Hidayat et al., 2015; Pramudya et al., 2017), to whom most scheme smallholders sell their harvest. This interdependence exposes them to price decisions made by the mills, thus making them susceptible to market fluctuations. Farmers who own a bank account, however, experience a statistically significant negative association with the price difference before and after the ban. Owning a bank account, a key aspect of smallholders' financial inclusion, indicates their access to financial services, which are crucial instruments for building resilience ahead as well as coping with adverse shocks (Demirgüç-Kunt & Klapper, 2013).

The farmer's household size, having oil palm cultivation as a primary income source, farmer's monthly average income from oil palm, and a dummy indicating whether the farmer has parts of the plantation certified decrease the price difference before and after the ban statistically insignificantly. Including fixed effects, led to a negative and statistically significant association of farmer's monthly average income from oil palm on the price difference. A dummy indicating that a farmer has the whole plantation certified, and a dummy indicating the farmer has any plantation certified under ISPO led to a statistically insignificant decrease of the price difference before and after the ban. One explanation could be that certified farmers achieved higher prices before the export ban than non-certified farmers, leading to an absolute larger reduction in prices. However, the relative price difference for the certified farmer is smaller than for non-certified farmers.

Column (3) presents the results without fixed effects and column (4) presents the results, including regional fixed effects for the minBIC Lasso. Only two variables have been selected. A statistically significant positive association exists between the farmer's primary income source being off-farm labour and a larger price difference before and after the ban. Having a bank account lead to a statistically significantly negative association on the price difference. Comparing the results to column (1) and (2) highlights no qualitative differences.

Column (5) presents the results without fixed effects and column (6) presents the results including regional fixed effects for the adapative Lasso. If the primary income source of the farmer is off-farm labour and being a female farmer led to a statistically significantly positive association on the price difference before and after the ban. Having a bank account led to a statistically significantly negative association on the price difference. The farmer's household size, reliance on oil palm cultivation as their primary income source, the farmer's average monthly income from oil palm, and a dummy variable indicating whether the farmer has partial plantation certification all led to statistically insignificant decreases in the price difference before and after the ban. Including fixed effects, lead to a negative and statistically significant association of farmer's monthly average income from oil palm on the price difference.

Table 4: Post-Lasso OLS for different Lasso algorithms.

	(1) cv	(2) cv	(3) minBIC	(4) minBIC	(5) adaptive	(6) adaptive
Dummy if primary income source is off-farm labour	184.80***	194.60***	324.70**	333.00**	183.00***	189.70***
	(9.95)	(7.45)	(55.69)	(57.41)	(9.53)	(7.21)
Dummy if farmer has a bank account	-176.60**	-158.60**	-235.20**	-224.10**	-202.00**	-192.30**
	(33.12)	(34.80)	(42.34)	(41.05)	(26.90)	(26.21)
Farmers' gender	147.20**	141.30**			153.1**	149.80**
	(27.65)	(24.79)			(31.32)	(29.18)
Farmer's household size	-43.89	-45.66			-38.48	-39.06
	(23.23)	(24.12)			(19.21)	(19.56)
Dummy if primary income source is oil palm cultivation	-111.70	-119.30			-115.00	-121.80
	(71.27)	(69.30)			(63.17)	(61.13)
Farmer's monthly average income from oil palm	-29.56	-30.63*			-30.93	-31.74*
	(10.36)	(9.43)			(10.68)	(10.10)
Dummy if farmer has all plantation certified	80.07	27.22			152.30	126.10
	(195.20)	(174.08)			(157.00)	(143.60)
Farmer's age	-0.03	0.00			-0.04	-0.01
	(0.06)	(0.08)			(0.06)	(0.08)
Dummy if farmer has any ISPO plantation certified	0.75	28.54			-30.94	-14.37
	(95.01)	(85.56)			(91.57)	(85.75)
Dummy if farmer has partly plantation certified	-91.26	-107.40				
	(48.83)	(49.84)				
Dummy if farmer or farmers parents are trans migrants	86.24*	108.30**				
	(21.02)	(24.92)				
Regional FE	No	Yes	No	Yes	No	Yes
R^2	0.095	0.102	0.055	0.059	0.088	0.092
N	383	383	383	383	383	383

Notes: Dependent variable is the price difference before and after the ban. Clustered standard errors on district level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusion

The Indonesian government's unprecedented decision to ban exports on palm oil in response to soaring cooking oil prices had considerable implications for Indonesian smallholder farmers. This study utilises primary data to explore how oil palm smallholders have been affected by this policy intervention. Oil palm smallholders are of particular interest because they were uniquely affected by the export ban as both consumers and producers. As consumers, they struggled with rising cooking oil prices, while as producers, they experienced volatile farm gate prices. The impact of the export ban on smallholders' livelihoods was investigated through reported price differences for fresh fruit bunches before and after the ban.

Employing descriptive statistics and the ML technique Lasso, we are able to answer our initially posed research questions: Firstly, what is smallholders' perception of the export ban, and secondly, are there differences in smallholders' vulnerability to price fluctuations with varying levels of endowments or access to resources? Regarding the first research question, we can state, that the majority of farmers did not view the government's export ban as a good idea. Additionally, most associated higher household expenses and lower farm profits with the ban. When asked about the price determination, many farmers believed it to be influenced by the Indonesian government. Regarding the perceived cooking oil prices, some noticed changes before the ban, but not many perceived a decrease in prices following the ban. However, a considerable proportion acknowledged the positive effect of cheaper cooking oil, outweighing the decline in fresh fruit bunch prices. Moreover, most farmers stated they maintained their usual food consumption patterns after the export ban, indicating a certain level of resilience despite price fluctuations. Overall, these findings highlight the complexities and trade-offs faced by farmers in the palm oil industry following the export ban.

Answering our second research question, we identified several factors that impact how smallholders are affected by the export ban on palm oil to answer our second research question. Farmers with a primary income source from off-farm labour and female farmers were more likely to experience larger price fluctuations following the ban. This could be due to limited access to resources or negotiating power within a male-dominated palm oil industry. However, having a bank account was associated with less pronounced price fluctuations, suggesting that financial stability may provide some level of protection against market risks. In contrast, transmigrant farmers, who were more closely integrated into the agricultural development, were more susceptible to the price decisions of mills, potentially due to their dependency on these actors. Overall, our findings underscore the diverse impacts of the export ban on different groups of smallholders, highlighting the need for tailored policies and support measures to mitigate the challenges faced by vulnerable farmers within the palm oil industry.

Our study offers fresh insights into the trade-offs between oil palm smallholders and palm oil consumers in the context of export bans. Our results highlight the crucial need to incorporate considerations for the overall well-being of smallholders in the development of policies within the palm oil industry Jelsma et al. (2019). These findings are relevant to both industry stakeholders and policymakers, highlighting the necessity of thoughtful policy implementation. Trade policy measures, including export bans, demand meticulous consideration to avoid unintentionally disrupting domestic market dynamics, which can lead to unintended consequences. Future research could explore the potential of decentralised refineries as a means to better integrate smallholders and as an instrument to increase their agency within the palm oil industry.

One potential limitations of this study might be that our primary dependent variable relies on a retrospective question regarding the last price for an FFB before the export ban. Panel data that captures precise prices and underlying factors would undoubtedly be more valuable in analyzing the factors influencing the trade ban. Second, given that we only have data from the Jambi province, our analysis is geographically restricted. Having data from additional states would enable a more comprehensive analysis.

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