Mining and Forest Loss*

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Abstract

In this study, we use global datasets to estimate the impacts of mining on forest loss. Comparing forest loss around mines with forest loss around random forest spots, we estimate that an area almost twice the size of Austria has been cleared due to mines worldwide. The extent of forest loss is decreasing with the distance to the mine, but there is significant forest loss even 15 km from the mines. This finding is consistent with mining activities occupying previously forested land directly. We also demonstrate that increased commodity prices lead to a reduction in forest loss. This is particularly true at roads in the vicinity of mines in low-income countries. This finding is consistent with an indirect effect of mining on forests, as a booming mine drags labour out from land intensive-industries and into mining. While mining pose local environmental threats to forests, resulting local economic development and structural change can reduce the pressure on the forest.

Keywords: structural change, deforestation, commodity prices

JEL-codes: J43, O13, O14, Q15, Q17

1 Introduction

The demand for minerals, such as coal, copper, but also rare-earth elements, is rising. Manufactures of many kinds, are based on these resources. Also abatement technologies, i.e. technologies which reduce the environmental pressure for example in terms of fossil fuel demand, are decomposed of minerals. Mineral extraction (mining), however, causes

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environmental damages on its own. Contamination of the soil, groundwater and surface water, deforestation and the corresponding loss of biodiversity, risk of erosion and threat to indigenous people’s habitat are a few of the reasons why the outcry of scientist, journalists and the society was huge when Brazil’s president Michel Temer in August 2017 abolished the protected area status of the Renca reserve, an area larger than Denmark located in the Amazon, to open up for mining. In this study, we set up a global data set to analyze the environmental damage in terms of forest loss associated with mining worldwide. In comparison to so-called random points an area almost twice the size of Austria has been cleared around mines. Gold and uranium extraction account with 39% and 24% respectively for the largest share of forest clearance. Coal and copper follow with each 10% of total forest loss around all mines. While the extent of forest loss is decreasing with the distance to the mine, a significant correlation of clearance and mining is still measurable in 15 km distance to a mine. In contrast to this positive association between mining and forest clearance, we demonstrate that increased mining activity, instrumented for with commodity price changes, leads to a reduction in forest loss. Especially at roads in the vicinity of mines in low-income and lower-middle income countries1 forest clearance is reduced when commodity prices rise. Forest loss in high-income countries as well as forest loss in off-road areas in low-income countries is not affected by changes in the commodity price. (The reduction in forest loss in response to an increase in commodity prices can be thought of as the relocation from more land-intensive economic activity such as agricultural production or logging towards mining - a mechanism which is only relevant in developing countries.)

There is an abundant literature on case studies analyzing the environmental damages caused by the extraction of various minerals in certain countries (Literature!). For instance, major environmental threats of gold mining have been identified, especially in the developing world. Veiga et al. (2006) report on deforestation, acid mine drainage, and air and water pollution from arsenic, cyanide, and mercury contamination. Deforestation as the source or co-pollution of further environmental damage such as loss of biodiversity and contamination of soil and water has been at the core in numerous case studies. Specifically, large and small scale gold and silver mining have been found to cause deforestation - e.g. in the Peruvian Amazon (Asner et al., 2013, Swenson et al. (2011)), Suriname (Peterson and Heemskerk, 2001), Mexico (Studnicki-Gizbert and Schecter, 2010) and the DRC (Butsic et al., 2015). In a preceding study, we found that globally deforestation is linked with oil drilling (Krings et al., 2017). While it seems to be intuitive that mining activities are land-intensive and need clearance to conduct their operations, Wunder and Sunderlin (2004) argued that increased oil drilling activities reduced deforestation in five

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1from now on we refer to these two groups jointly as low income countries in contrast to high income countries which include also upper middle income countries.
countries out of eight countries in the analysis (XXX) as result of a so-called Dutch disease effect. They showed that oil price booms reduced agricultural activity which is more land-intensive than oil drilling and therewith decrease forest clearance. In other words, the opportunity costs of more land-intensive activity increases with more profitable oil drilling activity. In this study we present supporting evidence for both hypotheses stated in the literature. On the one hand, we estimate that forest clearance to enable mining activity on a global level has summed up to an area almost twice the size of Austria. On the other hand, increased mining activity is associated with a decrease in forest loss supporting the “Dutch-disease effect” defined by Wunder and Sunderlin (2004).

Building on these different findings in the literature on forest loss in the context of mineral extraction, we aim at establishing a global relationship of mining and forest loss. We contribute to the existing literature in two steps. First we extend the numerous case studies on environmental hazards of resource extraction. There is an enormous literature on the general relationship of economic development and the environment (...). Acknowledging the importance of forests and in order to empower the REDD+ program, deforestation has been addressed specifically and the numerous drivers of deforestation have been disentangled, a.o., by Busch and Ferretti-Gallon (2014). To admit, while agricultural activities and proximity to cleared areas and roads have been identified as major causes of deforestation, mining and fossil fuel extraction do not account for the lion share in this concern. However, neglecting the coinciding of mining and forest loss would understate its importance in the light of the expected increasing demand for minerals in the future. In this regard, we provide a global overview of the extent of forest lost associated with mining.

In a second step, we identify the causal relationship of mining activities and deforestation. We build on previous literature that established a positive relationship of commodity prices and mining activity. Swenson et al. (2011) established that mining deforestation in the Peruvian Amazon as well as Peruvian mercury imports have increased with the rising gold price since 2003. Dube and Vargas (2013) refer, in the different context of resource conflicts, to these rising commodity prices as rising opportunity costs of economic activities different than resource extraction. In line with Dube and Vargas (2013) and others, we use commodity prices to instrument for mining activity to analyze the consequences for the forest due to increased mining activity. We distinguish the environmental consequences for areas at roads surrounding or leading to a mine and remote off-road areas. Similar to the dynamic panel model applied by Acemoglu et al. (2016), we establish a negative long-run relationship of mining activity and forest loss at roads in developing countries while accounting for the dynamics of deforestation and the effect of past changes in commodity prices. Moreover, this model allows us to control for mine fixed effects and global time-variant developments.
The next section presents the dataset for both steps of our analysis. We limit this analysis to forest loss as indicator for the environmental damage associated with mining activities. In contrast to other environmental hazards which can be attributed to mining, forest loss can be observed for a considerable time period on a global level. Basing its measurement on satellite pictures reduces heterogeneity in measurement across countries and time. It further enables to include observations from remote locations in the sample. To present a global estimate for the forest cleared due to mining we observe the vicinity of all mines located in forested areas worldwide and compare these with random points which form our control group. In addition to this cross-sectional analysis, a panel dataset allows to analyze the annual forest loss between 2001 and 2014 associated with price changes of minerals. Section III introduces the methodology applied for each step in this analysis and Section IV shows the results of our study. We conclude by putting our findings into the context of the existing literature.

2 Data

We put together a rich dataset to analyze the amount of forest clearance around mines worldwide.

Mining The information on the location and primary extracted commodity of 34,598 mines distributed across 157 countries is commercially available from SNL (Source?). In our analysis we distinguish between the main primary commodities which are gold (38% of all mines), coal (15%), copper (12.5%), iron (5.5%), U3O8 (5%), diamonds (4.2%), nickel (3.5%), silver (3.1%), zinc (3%), and others (remaining 10.2%). Furthermore, the dataset entails additional information such as the development and activity status of a mine, the type of extraction, i.e. openpit vs underground mining, starting and closing year, and operating company. This information is however far from complete and can therefore not be used for our global analysis.

Forest Hansen et al. (2013) provide data on global forest cover in the year 2000 and total as well as annual forest loss for the period 2001-2014 based on 30m x 30m images from the Landsat satellite. The extent of tree cover is defined as the percentage of these 30m x 30m pixels that is covered by vegetation taller than 5m. A distinction on the type of vegetation is however not possible. Forest loss is defined as a change from forest to non-forest of a given pixel. We generate three distinct variables to measure the forest in the areas of concern. First, the treecover variable tree is created. For each identified area surrounding a mine, the percentage of tree cover in the year 2000 is calculated as
the average tree cover of the pixels in this area. Second, the share of pixels situated within each defined area that experienced forest clearance at least once between 2001 and 2014 is generated as deforestation, \( df \), in percent. Finally, the same measurement of deforestation, \( df \), in percent of each area is generated likewise for annual clearance.

**Areas of interest** Considering the immediate as well as distant vicinity of a mine, the surrounding area with varying distances is analyzed regarding its forest loss. These surroundings are subdivided into seven *donuts* with radii of 100-500m, 500m-1km, 1-2km, 2-5km, 5-7km, 7-10km and 10-15km. Additionally, two circles with a radius of 100m and 20km mark the closest vicinity and the largest buffer around each point. Finally, we look at the roads running through each of these areas and generate the forest loss at 1 km distance to each of these roads obtained from Global Roads Open Access Data, Version 1, provided by SEDAC/CIESIN. Accuracy of the roads positions is stated to range between 30m to 500m. Therefore, we are confident to capture the behavior at the roads when taking a 1km buffer to both sides of each road. A distinction between the buffer around the mine and the vicinity of the road is not possible for the areas with radii below 2 km. This closest vicinity is therefore not considered in the distinction between roads and non-road areas.

**Commodity prices** The SNL dataset does not allow to observe actual mining activity each year at each mine. Following, Dube and Vargas (2013) and others, we instrument for economic activity at the mine with the variation in commodity prices which are retrieved for the years 2001 - 2014 for eleven minerals from the pink sheet of the World Bank.\(^2\) For the primary commodity extracted at each mine, an annual commodity price index with the base year 2001 is calculated and attributed to the respective mine. The eleven minerals reported by the World Bank cover 76% of all primary commodities in the dataset. As pictured in figure 1, prices on average quintupled in the period between 2001 and 2011 before decreasing back to an average level of the fourfold of 2001. During this period every commodity experienced an overall increasing trend with an unanimous drop during the global crisis 2009 and cooling off after 2011.

**Sample** To analyze the impact of mining on the forest the question is, how much deforestation would have happened if mining had not taken place. Since the location of mines cannot be considered to be random the causality of mining to forest clearance is hard to quantify. We conduct our analysis in two steps to estimate the amount of deforestation associated with mining. First, deforestation around a mine is compared to deforestation at different locations, i.e. random points form the control group. Hence, in \(^2\)the eleven minerals are: coal, copper, gold, silver, platinum, nickel, zinc, tin, lead, aluminum, and iron ore.
addition to 34,598 mines 27,903 onshore random points are generated worldwide. Figure 2 shows the distribution of all mines (left-hand panel) and onshore random points (right-hand panel) in our data. The sample of mines and random points chosen is limited to locations in the forest. Hence, the control group is generated randomly conditional on its surrounding forest cover to provide similarity to the locations of the mines. Based on biomes defined by SEDAC (2013) and measured in 5 arc-minute cells, i.e. approximately ten kilometers at the equator, 10,592 mines and 9,207 random points are identified to be situated in areas of woodlands or wild woods. These mines are spread across 97 countries. In robustness checks, the sample is reconsidered based on positive tree cover from Hansen’s data. Considering the area two to five kilometers distant surrounding each mine with a tree cover above 20%, 15,957 mines and 10,725 random points are included in the sample. 17,661 mines and 13,212 random points have a positive tree cover of more than 1% in the direct vicinity 100m radius. These samples include between 118 and 123 countries. Moreover, eight distinct distances of vicinities - i.e. the seven donuts and the 100m circle - are analyzed for each mine and random point.

The pink sheet of the world bank provides commodity prices for eleven minerals which cover 76% of our mines located in the woodlands or wild woods. In the baseline panel dataset defined according to SEDAC location in the woodlands and wild woods, this leaves us with 8,639 mines over the years 2001 to 2014, giving us 120,946 observation.
mines biomes: urban areas villages croplands rangelands woodlands barren lands

Figure 2: Mines and random points in our data
3 Methodology

We determine the global relationship of mining and forest loss in two distinct steps. First, we estimate the amount of deforestation due to mining by comparing forest loss in the surroundings of a mine with deforestation at random points located in comparable areas. We observe heterogeneity in the distance to a mine, the different commodities extracted and analyze the variation across locations. The random points chosen are comparable to the location of the mines in terms of their forest cover in the year 2000 and the biome identification in the direct vicinity of the coordinates given.

When estimating the regression equation

$$df_{id} = \beta_0 + \beta_1 \times mining_i + \epsilon_i$$

(1)

with standard ordinary least squares $\beta_1$ gives the percentage of forest cleared per buffer $d$ around point $i$ if the dummy $mining$ turns one. Under the assumption that, on average, random points and mines are identical locations, $\beta_1$ gives the excess deforestation due to mining over random points. The dependent variable $df$ measures average forest loss between 2001 and 2014 in percent surrounding a certain spot $i$ in various distances $d$. The explanatory variable $mining$ has, however, no information on the timing of its activity. $\epsilon_i$ covers all unobservables that could have an additional influence on deforestation. The potential of a correlation between $\epsilon_i$ and the variable $mining$ yields an obvious threat for a possible bias in the estimator.

In regression equation 2 we augment the analysis to exploit the variation if deforestation surrounding the mines across different primary commodities $c$ extracted. The reference point is no commodity extracted, i.e. a random point.

$$df_{icd} = \beta_0 + \sum \beta_c \times commodity_{ic} + \epsilon_i$$

(2)

However, the lack of annual operation data of each mine makes the point of causality from mining towards forest clearance prone to argumentation. In line with previous studies, such as Dube and Vargas (2013), we use annual commodity prices to instrument for the economic activity at a mine. Annual world prices can be considered to be exogenous to each single mine. We estimate

$$df_{mtd} = \beta_0 + \beta_1 p_{mt} + a_m + u_t + \epsilon_{mt}$$

(3)

to analyze the impact of annual price variation of the primary commodity at each mine.
$m$ on the annual forest loss at various distances $d$ around each mine. $p_{it}$ is the logarithm of the annual price index coded 1 in 2001 as the base year. The set-up of a panel dataset and the application of a within estimator allows to control for mine fixed effects $a_m$ and year fixed effects $u_t$ to exclude time-invariant factors such as geography and global shocks such as the implementation of the REDD+ program or prices of timber to bias the $\beta_1$ estimator. The error term $\epsilon_{it}$ covers all other time-variant unobservable effects on deforestation at each mine. The baseline estimate is calculated for the area of 20 km radius around each mine. Additionally, the economic activity in the vicinity of a mine is analyzed by limiting the areas to roads crossing through this vicinity versus deserted off-road areas.

Theoretically, it is unclear if prices have an immediate effect on the forest clearance or if there is a lagged effect. Along the lines of Acemoglu et al. (2016), we employ a dynamic panel model for deforestation to identify a long-run effect from changes in commodity prices on deforestation around mines. We again use the standard within estimator to control for mine fixed effects $a_m$ and year fixed effects $u_t$. We include lagged values of both variables, indicated with the $L_1$, to control for the dynamics in deforestation and the effect of past developments in commodity prices on deforestation. Moreover, figure 5 demonstrates that commodity prices and deforestation do not follow stationary processes. Under the assumption of a unit root we take first differences, notated with a $D_1$, of both variables, deforestation and commodity prices, to control for spurious correlation. In essence, we use the standard within estimator to estimate the error correction model

$$df_{mt} = \beta_0 + \beta_1 \times Df_{m,t-1} + \beta_2 \times Dp_{t-1} + \beta_3 \times p_{t-1} + \beta_4 \times Df_{m,t-1} + a_m + u_t + \epsilon_{mt} \quad (4)$$

where the long-term effect of a price change on deforestation is defined as

$$\frac{\beta_3 + \beta_4}{1 - \beta_1 - \beta_2}. \quad (5)$$

4 Results

The first step of this analysis compares random points located in forest areas to mines and looks at the area of forest loss surrounding both of these spots with increasing distance. The left panel of figure 3 shows a convincingly constant and lower average amount of forest lost between 2001 and 2014 in the vicinity of random points in comparison to the vicinity of mines. The figure compares the average rate of deforestation in each buffer surrounding a mine to the same buffers surrounding random points. The figure also shows a steadily decreasing amount of each area cleared the larger the distance to the mine. Estimating the relationship of mining and deforestation presented in equation 1, the right panel of figure 3 visualizes the coefficients presented in table 1 and shows
that the difference in deforestation between random points and mines is positive and significant at the 5% level for all areas considered. However, the impact of mining on forest loss decreases gradually with the distance to the mine. As expected, the adjusted $R^2$ is very low giving little explanatory power to mining activities for the heterogeneity in deforestation across locations. The size and significance of the coefficients is practically identical if the sample of 15,957 mines and 10,725 random points which are located in areas with more than 20% of tree cover at 2 to 5 km distance around each spot. (possibly Appendix)

Despite the methodological drawbacks, the positive correlation of mining and forest clearance surrounding the mine seems obvious due to controlling for the spatial dimension. Adding to this, figure 4 shows that the extent of forest lost around a mine varies with the commodity extracted. The estimates $\beta_c$ of equation 2 show a heterogeneity in the degree of clearance across different commodities. Compared to the random points, a positive impact of each commodity on forest loss is displayed. The impact is largest and significant for coal and uranium (U3O8). Mines extracting copper, gold, and nickel only have more forest loss than random points in the direct vicinity. The dimension of these mines seems to be smaller than for coal and uranium. Again, the impact decreases with increasing distance to the mine.

Table 1: Deforestation due to mining over distance to the mine

<table>
<thead>
<tr>
<th></th>
<th>(1) loss001</th>
<th>(2) loss001_005</th>
<th>(3) loss005_01</th>
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<th>(5) loss02_05</th>
<th>(6) loss05_07</th>
<th>(7) loss07_10</th>
<th>(8) loss10_15</th>
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<td>mining</td>
<td>0.0556***</td>
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<td>0.0227***</td>
<td>0.0180***</td>
<td>0.0159***</td>
<td>0.0108***</td>
<td>0.0119***</td>
<td>0.00971***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
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<tr>
<td>Mines</td>
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<td>24999</td>
<td>24999</td>
<td>24837</td>
<td>24649</td>
<td>24320</td>
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<td>Adj.R2</td>
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<td>0.00765</td>
<td>0.00721</td>
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<td>0.00663</td>
<td>0.00376</td>
<td>0.00471</td>
<td>0.00374</td>
</tr>
</tbody>
</table>

$p$-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Summing up the area of forest lost due to each commodity, roughly 150,000 km$^2$ are accumulated$^3$. That is the land area of Tunisia or twice the size of Ireland (almost twice the size of Austria). Table 2 shows gold and uranium extraction account with almost 39% and 24% respectively for the largest share of forest clearance. Coal and copper follow with each 10% of total forest loss around mines. Table 1 displays the impact of mining on the forest in different distances to the mine. This decomposition in forest loss per commodity is in line with the finding of the right-hand panel of figure 3 and table 1, where the impact of mining is positive and significant up to 15 km distance when compared to a control group of random points. Summing up the estimated impact of each area for 10,592 mines, a total of 150,977.78 km$^2$ is explained by mining.

Heterogeneity across countries does not follow any obvious pattern - see excel: Overview sample.

In a second step, we make use of the annual variation in commodity prices to instrument for the economic activity at a mine. The commodity prices provide a channel to analyze the causality running from mining to deforestation by accounting for yearly variation in forest loss and mining activities. We use the largest area of our analysis, i.e. the 20 km radius and distinguish additionally between the area at roads and off-roads. As

$^3$The estimated area cleared does not change when only including significant estimators.
<table>
<thead>
<tr>
<th>commodity</th>
<th>number of mines in woodlands</th>
<th>area lost in km$^2$</th>
<th>significant area lost in km$^2$</th>
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<td>4,440</td>
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<td>59,114.53</td>
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<tr>
<td>U3O8</td>
<td>549</td>
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<tr>
<td>others</td>
<td>1,119</td>
<td>13,558.28</td>
<td>13,558.28</td>
</tr>
</tbody>
</table>

| $\sum$    | 10592                       | 150,573.89         | 151,896.57                  |

Notes: biomes are defined as the majority of pixels in the 500m - 15km radius around each mine according to SEDAC. Area lost is projected based on all vs only significant estimators per “donut”.

Table 2: Total area of forest lost across primary commodities extracted
explained in equation 3, estimating the impact of a price increase on deforestation while controlling for mine and year fixed effects, gives an overall negative relationship which is significant at the 1% - level. As table 3 shows, this negative relationship is driven by low-income countries, while high-income countries show no significant relationship between commodity prices and forest loss.

Visually this impression can be supported by figure 5 where commodity prices and average forest loss move counter-cyclically in low-income countries - portrayed on the left-hand side - while forest loss seems to be less affected by the rise in prices of commodities extracted in high-income countries (right-hand panel of figure 5). Subdividing the area around each mine into the direct vicinity of roads leading to the mine and running through the area of concern versus remote areas o-roads allows a deeper insight into the economic activity in the surroundings of a mine. Figure 6 shows that the counter-cyclical movement of commodity prices and forest clearance in low-income countries is primarily driven by forest clearance close to roads. While forest clearance in remote areas does not respond to price movements and stays at a constantly lower level during the whole period of analysis. Forest loss in high-income countries seems to be independent of price movement of minerals. Both rates of forest loss - at roads and o-roads - are constant over time, albeit at a lower level in the remote areas.

However, especially the positive trend in both variables shown for low-income countries gives rise to the concern of autocorrelation. While it is unclear if prices of last period have a larger impact on forest clearance than this year’s prices, the long-term correlation of both variables is certainly of interest.

Applying the dynamic panel model introduced in equation 4 the long-term effect of a price increase of forest loss can be shown to be negative in low-income countries while no significant effect can be detected in high-income countries and over the whole sample. This long-term effect (shown in Tables 4) also supports the impression of figure 6 that this correlation is driven by the forest clearance in the direct vicinity of roads. Interestingly,
Figure 5: Commodity prices and forest loss in high and low income countries

even at roads no correlation between prices and forest loss can be observed in high-income countries. A variety of explanations come into mind to explain this phenomenon. Most likely, a combination of these is true. (1) High-income countries have better enforcements of environmental regulations which hamper avoidable forest clearance (see Krings, Cust and Harding 2017). (2) Logging, especially illegal logging, is less common in high income countries. Hence, opportunity costs of logging only rise in low-income countries with price increases of minerals. (3) The positive correlation of mining and forest loss due to the land-intensity of mining shown in the first part of this analysis and the negative correlation due to rising opportunity costs of more land-intensive economic activity off-set each other leading to an overall insignificant finding (why is this off-setting in high-income countries?).
Figure 6: Commodity prices and forest loss at and off-roads in high and low income countries

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| long-term effect | 0.0165   | 0.0324   | -0.161***| -0.0158841| 0.0220 | -0.225***| 0.0245 | 0.0222 | 0.083 |
|                 | (0.935)  | (0.134)  | (0.000)  | (0.568)  | (0.453) | (0.005)  | (0.359) | (0.441) | (0.568) |

| N              | 103620   | 93540    | 9687      | 73896    | 65160  | 8568    | 73896  | 65160  | 8568  |
| r2             | 0.463    | 0.468    | 0.418     | 0.531    | 0.537  | 0.498   | 0.519  | 0.524  | 0.491 |

p-values in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4: Error correction model
References


