Economic Dynamics and Forest Clearing

A Spatial Econometric Analysis for Indonesia

David Wheeler, Dan Hammer, Robin Kraft, Susmita Dasgupta, and Brian Blankespoor

Abstract

This paper uses a large panel database to investigate the determinants of forest clearing in Indonesian kabupatens since 2005. Our study incorporates short-run changes in prices and demand for palm oil and wood products, as well as the exchange rate, the real interest rate, land-use zoning, forest protection, the estimated opportunity cost of forested land, the quality of local governance, the poverty rate, population density, the availability of communications infrastructure, transport cost, and local rainfall and terrain slope. Our econometric results highlight the role of dynamic economic factors in forest clearing. We find significant roles for lagged changes in all the short-run economic variables—product prices, demands, the exchange rate and the real interest rate—as well as communications infrastructure, some types of commercial zoning, rainfall, and terrain slope. We find no significance for the other variables, and the absence of impact for protected-area status is particularly notable. Our results strongly support the model of forest clearing as an investment that is highly sensitive to expectations about future forest product prices and demands, as well as changes in the cost of capital (indexed by the real interest rate), the relative cost of local inputs (indexed by the exchange rate), and the cost of land clearing (indexed by local precipitation). By implication, the opportunity cost of forested land fluctuates widely with changes in international markets and decisions by Indonesia's financial authorities about the exchange and interest rates. Our results suggest that forest conservation programs are unlikely to succeed if they ignore such powerful forces.

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1. Introduction

Forest clearing is an enormous contributor to global warming, accounting for some 15% of annual greenhouse gas emissions (WRI, 2010). Most forest clearing occurs in developing countries that have limited resources and regulatory capacity. Since these countries understandably focus their energy and resources on poverty alleviation, their support for forest conservation will be weak as long as forested land has a higher market value in other uses. Under these conditions, many actors will continue clearing their forested land unless they are given conservation payments that match or exceed the opportunity cost of the land. This economic insight has led to the establishment of REDD+ (Reducing Emissions from Deforestation and Forest Degradation in Developing Countries), a set of programs that help countries prepare for direct compensation schemes.

While the conceptual foundations of REDD+ are straightforward, its actual success will depend on program designs tailored to the economic dynamics of forest clearing in tropical forest countries. Stern (2006), Nauclér and Enkvist (2009) and UNFCCC (2007) have asserted that carbon emissions abatement from forest conservation is generally lower-cost than abating emissions from fossil fuels. For example, the UNFCCC's estimate of CO2 emissions from forest clearing (5.8 Gt) implies an average abatement cost of only \$2.10/tonne[1]. While such general estimates inform the policy dialogue, they cannot guide specific conservation programs because the economic returns to forest clearing vary widely over space and time (RFF, 2011). For many agents, land clearing for production is a lumpy investment driven by expectations about future prices and demand conditions. These expectations and investor interest in land clearing will change with market conditions, creating problems for REDD+ incentive programs based on fixed payments, or traditional forest conservation programs that focus on protection of designated areas.

Extensive theoretical work has considered the role of economic dynamics in forest clearing. However, relevant empirical research has been severely hindered by the lack of spatially-disaggregated time series data. Until recently, the translation of satellite images into credible estimates of forest clearing has been so cumbersome that updates have taken years for many countries. As a result, empirical research has focused on multi-year clearing and its

1. This estimate is based on the opportunity cost of forested land.

relationship to demographic and geographic factors. The forced exclusion of fluctuating economic conditions from most studies has left researchers and policymakers uncertain about the timing, magnitude and spatial incidence of their effects. At the same time, long lags in forest monitoring have left conservation managers blind to new threats in many areas, and program evaluators unable to provide timely assessments of conservation measures.

Faced with these limitations, donors and governments have traditionally focused on legally-protected areas, hoping (without much empirical support) that they could defend fixed conservation frontiers without accurate monitoring information. However, this low-level equilibrium is now threatened by massive REDD+ payment programs that will force donors to account for billions in expenditure for targeted reductions of carbon emissions from forest clearing. Such programs are not likely to survive taxpayer scrutiny unless they incorporate much more accurate and timely information.[2]

Fortunately, the state of the art in forest monitoring is now advancing rapidly. Work by Hansen et. al (2008), Souza (2006), Townshend, et al. (2008), Hammer, et al. (2009), Asner (2009), Jarvis (2009) and others is creating new, high-resolution forest information systems based on NASA's MODIS (Moderate Resolution Imaging Spectrometer) and Landsat programs, as well as airborne light detection and ranging (LiDAR). Drawing on advances for the MODIS system, Hammer et al. (2009) have recently published FORMA (Forest Monitoring for Action), a monthly database for forest clearing in Indonesia at 1 km resolution since 2005.

Equipped with the vast new information resource available from FORMA, this paper focuses on Indonesia for an in-depth econometric study of economic dynamics and forest clearing at a high level of spatial and temporal disaggregation. Economic dynamics are clearly important for the Indonesian case, which is heavily driven by forest clearing for palm-oil and wood-processing exports to fast-changing Asian markets.

The remainder of the paper is organized as follows. Section 2 reviews the extensive prior research on the economics of forest clearing. In Section 3 we discuss past limitations imposed by data scarcity, and the implications of recent technical advances for expanded research in this domain. Section 4 introduces the FORMA database, a critical contributor to the expanded prospectus, and uses FORMA data to investigate patterns of national and local forest clearing in Indonesia since 2005. In Section 5, we develop a model of forest clearing based on expected profitability calculations by potential investors in commercial production on currently-forested land. Section 6 describes the available data and Section 7 specifies a model for econometric panel estimation. We present and discuss our econometric results in Section 8, while Section 9 summarizes and concludes the paper.

2. In addition, land which is most appropriate for REDD+ programs may not be in currently-protected areas.

2. Prior Research

Previous empirical research has assessed the relative importance of numerous factors that may influence the conversion value of forested land. These include local population scale and density, distance from markets, the quality of transport infrastructure, agricultural input prices, physical factors such as topography, precipitation and soil quality, and zoning into categories that include protected areas. The results are generally consistent with a model in which the conversion of forest land varies with potential profitabliity.[3] Among studies that control for protection zoning, Nelson and Chomitz (2009) provide the most rigorous and comprehensive assessment. Their finding for the tropical forest biome -- that protected areas have less land clearing, ceteris paribus -- supports the specific results of Gaveau, et al. (2009) for Sumatra, Indonesia.

The existing research provides many useful insights about long-run drivers of forest clearing. Nelson and Chomitz (2009) and Rudel, et al. (2009) have studied land-use change across countries over multi-year intervals. Within counties, numerous econometric studies have estimated the impact of deforestation drivers across local areas during multi-year intervals. Some studies have used aggregate data for states, provinces or sub-provinces (e.g. studies for Brazilian municipios by Pfaff (1997) and Igliori (2006), and Mexican states by Barbier and Burgess (1996)). Many studies have also used GIS-based techniques to obtain multi-year estimates at a higher level of spatial disaggregation (e.g., Cropper, et. al. (1999, 2001) for Thailand; Agwaral, et al. (2002) for Madagascar; Deininger and Minton (1999, 2002), Chowdhury (2006) and Vance and Geoghegan (2002) for Mexico; Kaimowitz, et al. (2002) for Bolivia; and De Pinto and Nelson (2009) for Panama). In rarer cases, studies have used annual national or regional aggregate time series over extended periods (e.g. Zikri (2009) for Indonesia; Ewers, et al. (2008) for Brazil). These studies are hindered by limited degrees of freedom, since they must control for many factors and available observations are annual at best.

While econometric work on long-run forest clearing drivers is well-advanced, data problems have limited treatments of short-run economic dynamics to theoretical work and simulation modeling. Arcanda, et al. (2008) and others have studied the theoretical relationships between economic drivers and forest clearing. Notable simulation exercises include Cattaneo (2001) for Brazil and San, et al. (2000) for Indonesia. The latter study investigates economic drivers of forest clearing in Sumatra using a multisectoral, multiregional computable general equilibrium model. Since short-period data were not available to the authors, they use changes in deforestation-related sectors (e.g. plantation agriculture, wood products) as proxies. While the results are interesting and suggestive, they depend entirely on the researchers' specification of CGE parameters, and are unable to provide any estimates for areas smaller than provinces.

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3. For detailed summaries, see particularly Chomitz, et al. (2006); also Igliori (2006) and Wunder and Verbist (2003).

While more temporally- and spatially-disaggregated studies have been awaiting the advent of better data, econometric theorists have been laying the groundwork for efficient estimation of more highly-disaggregated models. Notable contributions to the literature on computable approaches to spatial econometric analysis have been made by Agarwal, et. al. (2002); Anselin (2001, 2002), Barrios, et al. (2010); Kapoor et al. (2007); and Kelejian et al. (1998, 2004, 2006).

3. Expanding the Scope of Work

3.1 Past Contributions

Many estimates of forest clearing are based on remotely-sensed data that have been available in various forms for decades. Perhaps the most impressive contribution has been made by Brazil's PRODES (2009), which has provided yearly maps of Amazonian forest clearing since 1988. Since 2004, these have been augmented by twice-monthly estimates from Brazil's DETER system.[4] Another noteworthy Brazilian contribution is Imazon's Forest Transparency Initiative, which has utilized MODIS data to produce and rapidly disseminate information about forest clearing in Mato Grosso State (Souza et al., 2009).

Several global-scale studies of forest clearing have been reported in scientific journals. Although they have laid the groundwork for global monitoring, these studies have not replicated the Brazilian contribution by providing updated, online reporting. Nor are they accessible to non-specialists who do not have a deep understanding of Geographic Information Systems (GIS) and remote sensing techniques. As Grainger (2008) has noted, tracking the long-term trend in tropical forest clearing has been problematic. Hansen, et al. (2008) identify global forest clearing in humid tropical forests using MODIS and Landsat images for the period 2000-2005. Mulligan (2008) uses remotely sensed data for assessment of land use changes in and around protected areas from 2000 to 2005. Carroll, et al. (2006) identify changes in vegetation cover from 2001 to 2005.

Several institutions provide detailed information on forest clearing with varying quality, but they have not attempted continuous global monitoring at high resolution. The FAO (2005, 2010) provides a detailed Global Forest Resources Assessment at the country level, updated at 5-year intervals. The World Resources Institute has published detailed maps of forest clearing hotspots in Latin America, Asia and Africa for the period 2000-2006. The website maintained by Global Forest Watch[5] provides global information, but with non-standardized spatial and temporal coverage of different datasets by country, infrequent updates, and a map interface that does not permit integrated global views. In summary, outside of Brazil,

4. Detailed descriptions of PRODES and DETER are available from Brazil's National Institute for Space Research (INPE) at http://www.obt.inpe.br/prodes and http://www.obt.inpe.br/deter.

5. Available at http://www.globalforestwatch.org/english/index.htm.

policy researchers have not been able to access panel databases sufficient for in-depth investigations of country-specific dynamics.

3.2 Recent Advances

Recently, a group affiliated with the Center for Global Development and the University of Maryland has laid the groundwork for a global database that will permit much more rigorous empirical work on the economic dynamics of forest clearing. Called FORMA (Forest Monitoring for Action), the system utilizes data recorded daily by the Moderate Resolution Imaging Spectrometer (MODIS), which operates on NASA's Terra and Aqua (EOS PM) satellite platforms. Although its signal-processing algorithms are relatively complex, FORMA is based on a common-sense observation: Tropical forest clearing involves the burning of biomass and a pronounced temporary or long-term change in vegetation color, as the original forest is cleared and replaced by pastures, croplands or plantations. Accordingly, FORMA constructs indicators from MODIS-derived data on the incidence of fires and changes in vegetation color as identified by the Normalized Difference Vegetation Index (NDVI). It then calibrates to local forest clearing by fitting a statistical model that relates the MODIS-based indicator values to the best available information on actual clearing in each area.

FORMA incorporates biological, economic and social diversity by dividing the monitored territory into blocks and separately fitting the model to data for the parcels in each block. The dependent variable for each pixel is coded 1 if it has actually experienced forest clearing within the relevant time period, and 0 otherwise. The MODIS-based indicator values are the independent variables. For all tropical countries except Brazil, the best identification of recent forest clearing has been published in Proceedings of the National Academy of Sciences by Hansen, et al. (2008), who provide estimates for 500m parcels in the humid tropics. FORMA is calibrated using the map of forest cover loss hotspots (henceforth referred to as the FCLH dataset) published by Hansen, et al. for the period 2000-2005.

Using the FCLH pan-tropical dataset for 2000-2005, FORMA fits the calibration model to observations on forest-clearing for 1 km^2 cells in each country and ecoregion. As Hammer, et al. (2009) document, the model's predicted spatial probability distribution provides a very close match to the spatial incidence of FCLH forest-clearing. FORMA then applies the fitted model to monthly MODIS indicator data for the period after December 2005. The output for each month is a predicted forest-clearing probability for each 1 km^2 parcel outside of previously-deforested areas, as identified in the FCLH map. FORMA selects parcels whose probabilities exceed 50%. It calculates the total number of selected parcels within a geographic area to produce an index of forest clearing activity in that area. Even small geographic areas can include thousands of 1 km cells, so error-averaging ensures robust index values.[6] FORMA's outputs consistently aggregate to forest-clearing indicators for subnational, national and regional entities.

This new dataset permits panel estimation of spatially-disaggregated forest clearing models that incorporate short- and medium-term economic dynamics, as well as previously-studied demographic and geographic determinants of forest clearing. It also permits explicit consideration of differences in clearing dynamics across land-use categories, including protected areas and areas zoned for commercial exploitation. The results can provide important new insights into the behavior of forest clearing agents who constantly adjust expectations as market conditions change.

Such econometric analysis can provide two major benefits for conservation policymakers and project planners. First, its incorporation of important economic variables will provide measures of their relative significance as drivers of forest clearing. By providing a better understanding of economic incentives in this context, the results will inform the design and implementation of incentive payment systems for REDD+ programs and similar arrangements. Second, the estimation of dynamic econometric models will provide a quantitative foundation for tracking area-specific risks of forest clearing as economic and other conditions change.

4. National and Regional Trends in Indonesian Forest Clearing, 2005–2010

The advent of monthly forest-clearing data permits a much more timely, detailed view of forest clearing than has previously been possible. In this section, we use the FORMA Indonesia database to develop a detailed view of forest-clearing patterns since 2005.

4.1 National Trends

Figure 1 displays FORMA-estimated indices for monthly forest clearing in Indonesia from December 2005 to December 2010. The graph indexes monthly changes on the left axis and annualized changes on the right axis. The monthly series displays marked seasonality; annualizing the data with a 12-month moving sum removes the seasonal component, revealing a broadly-declining trend during the past five years.[7]

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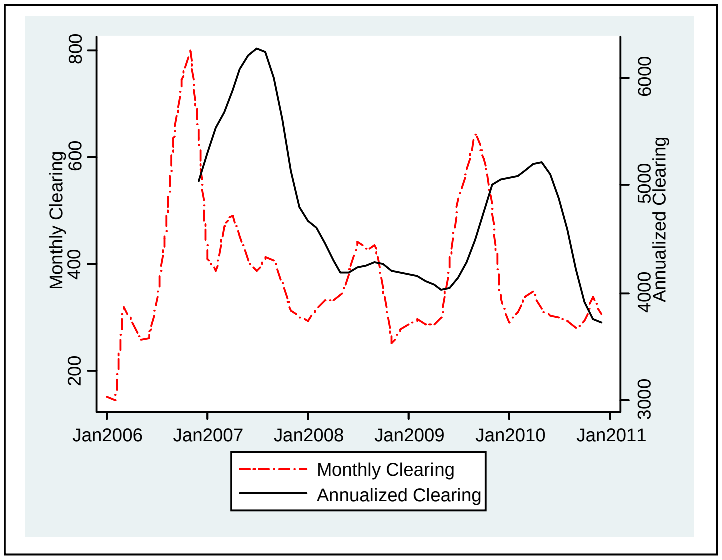
6. For example, a square area 50 km on a side contains 2,500 1 km cells.

7. The moving sum is equivalent to a 12-month moving monthly average, multiplied by 12. For each month, we compute the moving series using that month and the previous 11 months.

4.2 Patterns of Regional Change

Changes in the index of national forest clearing summarize complex patterns of change within Indonesia. In Figure 2, we investigate relative changes at the kabupaten level by dividing the total of monthly index values in 2010 by the total in 2006. We color the map dark for ratios greater than one (larger index values in 2010 than in 2006); lighter for ratios equal to one (no change); and lightest for ratios less than one (smaller index values in 2010).

Figure 1: Large-Scale Forest Clearing in Indonesia December 2005–December 2010



Clear interregional patterns are evident in Figure 2: Forest-clearing activity has increased in northern Sumatra and decreased in the southern and central parts of the island. Kalimantan exhibits increased activity in the west and north, and either constant or decreased activity in the south-central and eastern areas. Increased activity also appears in central Sulawesi, and parts of western and southern Irian Jaya.

Figure 2: Change in Forest Clearing Index Value: 2006 vs. 2010

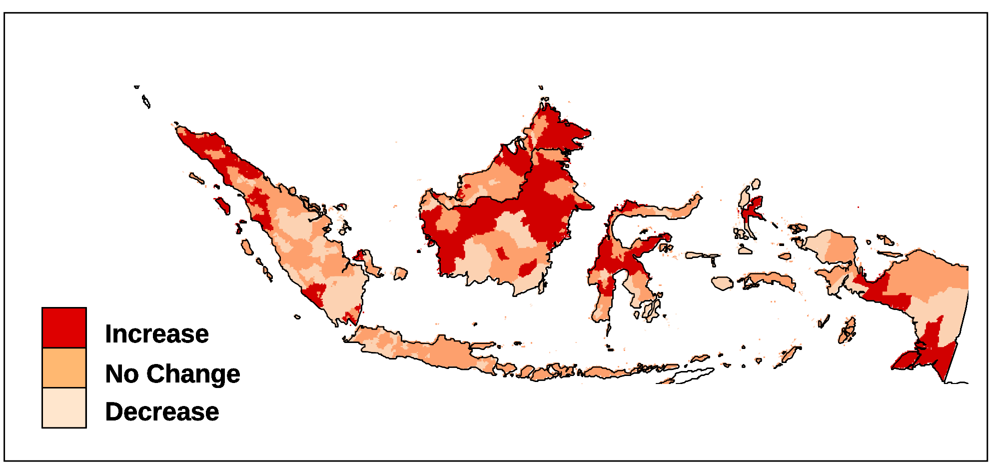


Figure 3: Sumatra and Kalimantan: Forest Clearing Rank of Kabupatens among 1,372 Secondary Administrative Units in Southeast Asia

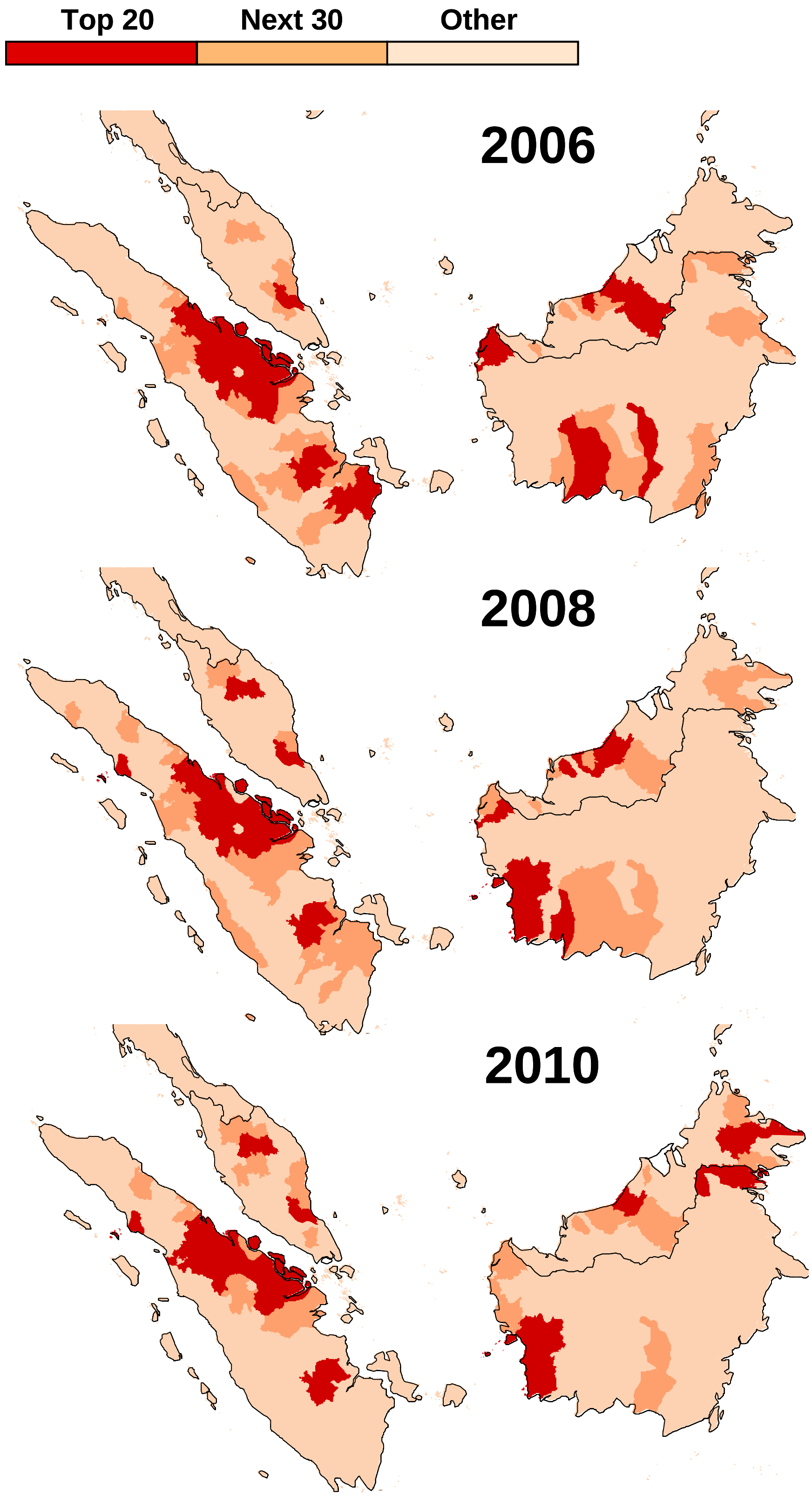


Figure 2 displays patterns of change without providing any information about the scale of activity. Figure 3 provides an alternative view by identifying Indonesian kabupatens whose index values are top-ranked among 1,372 secondary administrative units in Southeast Asia. On this map we color units dark if they are in the top 20, lighter if they are in the next 30, and lightest otherwise. In 2006, Indonesia's highest regional index values were concentrated in east-central Sumatra, southern Sumatra and south-central and extreme northwest-central Kalimantan.

Substantial changes are evident by 2008, with a reduction of top-ranked areas in southern Sumatra, some new areas in northern Sumatra, and a shift westward in southern Kalimantan. These patterns become more pronounced in 2010, with continued shrinking of the clusters in south Sumatra and southern Kalimantan, and increased cluster size in the northern frontier area of Kalimantan.

While parts of the pattern have significantly changed since 2006, some parts have also remained stable, with large top-ranking clusters persisting in east-central and southern Sumatra.

Indonesian provinces

4.3 Changes by Province and Kabupaten

Figure 4 illustrates trends in annualized forest-clearing indices for the five Indonesian provinces with the largest index values in January, 2007. In the first year, the series are dominated by the clearing indices of Riau (east-central Sumatra) and Central Kalimantan. The more recent period has witnessed strong convergence, with steep declines in both Riau and Central Kalimantan, along with increases in West Kalimantan and North Sumatra and a more modest decline (in absolute terms) in South Sumatra.

These changes are reflected in the overall patterns displayed in Figure 2. Riau has experienced the greatest decline, although it retains the highest index value in Indonesia. Within Riau, Figure 5 shows that convergence of kabupatens has also occurred. In January 2007, Pelalawan dominated the other top-ranking units in Riau. All five units have

Figure 4: Annualized Forest Clearing Index Values: Top 5 Indonesian Provinces in January 2007

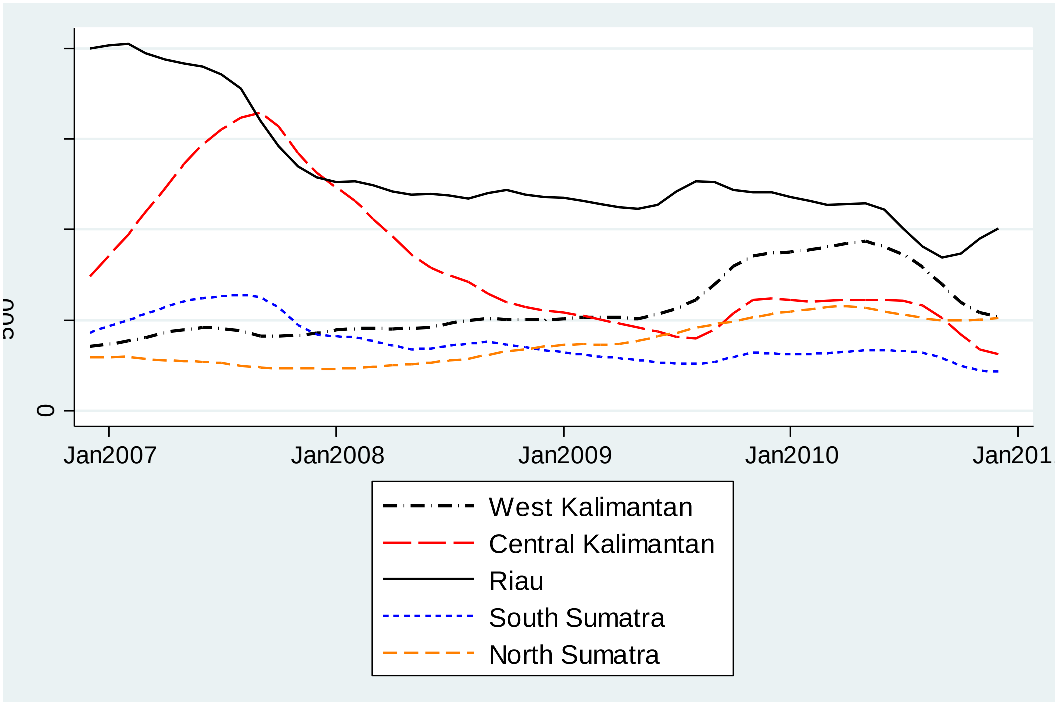
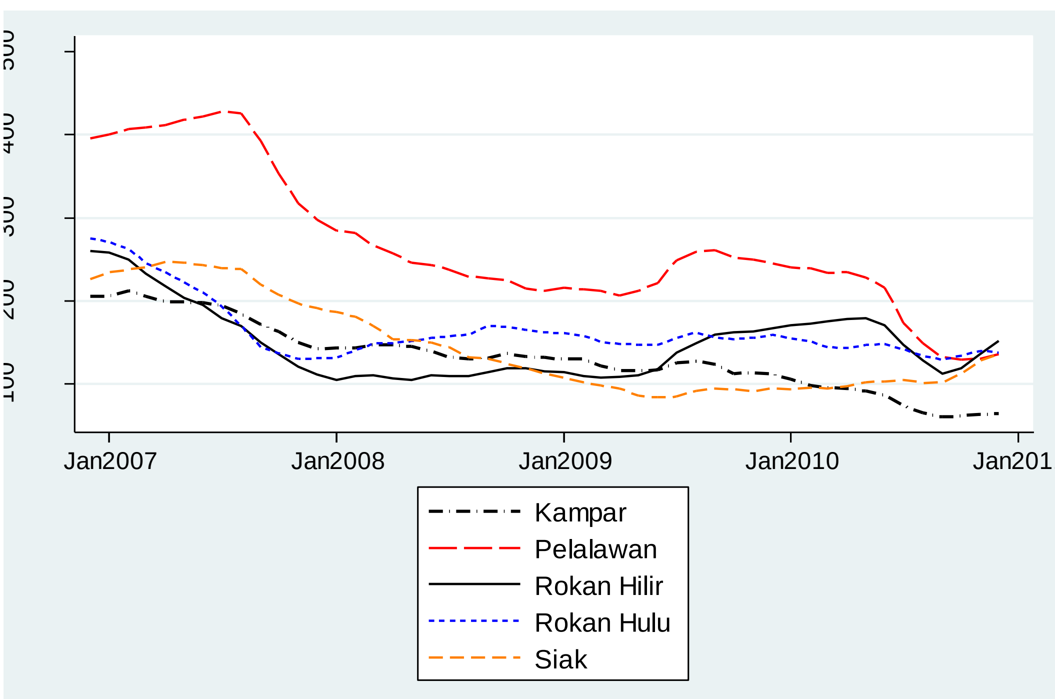


Figure 5: Annualized Forest Clearing Index Values: Top 5 Kabupatens in Riau



experienced a decline since then, but it has been most pronounced in Pelalawan. Slower declines in three of the other units (Rokan Hilir, Rokan Hulu and Siak) have brought them to approximate parity with Pelalawan.[8]

5. Model Specification

To explore the determinants of the patterns revealed by Figures 1-5, we mobilize a FORMA panel dataset for Indonesia that includes monthly observations on forest clearing from January 2006 to December 2010 for over 950,000 1-km parcels.[9] This dataset permits construction of a large panel database at the kabupaten level.

We posit an intertemporal model in which the representative proprietor or occupant of a forested area considers the relative profitability of maintaining or clearing the area. In each period, the agent compares the present-value profitability of sustainably-

harvested forest products with the clear-cut value of forest products, plus the cleared land's present-value profitability in its best use (e.g., plantation (palm oil, wood products), pasture, smallholder agriculture, settlement). Forest clearing dynamics are likely to be quite different in cases where commercial exploitation rights are well- or poorly-defined.

The decision to hold or clear a parcel depends on many factors, including expected revenues, input costs and the exchange rate. Expected revenues are a function of expected international prices and demand, particularly for wood products and palm oil in the Indonesian case. These factors and the exchange rate are constant across areas but vary over time, while other factors vary over both areas and time.

The relative significance of forest clearing determinants may well depend on the nature of particular forested areas, because they may be occupied by different types of agents with different incentives. A recently-produced GIS database enables us to separate Indonesia's forested land into areas zoned for activity in five categories: protected natural forest, palm oil plantations, timber plantations, logging concessions, and unzoned areas.

In our specification, the relative profitability of forest clearing for agriculture or settlement, for the representative proprietor or occupant in area i, time t, is given by:

(1) $$\pi_{it}^e = \pi_{it}^e(p_t^e, q_t^e, n_{it}, t_{it}, c_{it}, i_t^e, x_t^e, g_{it}, r_{it}, u_{it}, h_{it}, y_{it}, w_{it}, s_i)$$

Expectations: $\pi'(p^e)>0$, $\pi'(q^e)>0$, $\pi'(n)<0$, $\pi'(t)<0$, $\pi'(c)<0$, $\pi'(i^e)<0$, $\pi'(x^e)>0$, $\pi'(g)>0$, $\pi'(r)<0$, $\pi'(h)>0$, $\pi'(y)>0$, $\pi'(w)<0$, $\pi'(s)<0$

8. An animation of monthly forest-clearing in Riau using the FORMA probability map can be accessed at http://dl.dropbox.com/u/5365589/FORMA.zip.

9. Indonesia's natural forest area in 2000 was 951,160 sq. km. (WRI, 2010).

π	=	Expected relative profitability of forest clearing
p^e	=	Vector of expected prices for relevant products
q^e	=	Vector of expected demands for relevant products
n	=	Rupiah-denominated input cost per unit of output
t	=	Transport cost per unit of output
c	=	Communications cost per unit of output
i^e	=	Expected interest rate
x^e	=	Expected exchange rate (rupiah/dollar)
g	=	Quality of governance from investors' perspective
r	=	Regulatory quality
u	=	Officially-designated use (among the five categories specified above)
h	=	Population density
y	=	Unskilled wage rate
w	=	Precipitation (forest-burning is more difficult when rainfall is heavier)
s	=	Slope of the terrain

In this specification, the expected profitability of forest clearing relative to forest conservation increases with expected revenues for outputs produced on cleared land, which in turn depend on the expected prices and levels of demand for those outputs. Expectations adjust to changes in prices and quantities with product-specific lags. The expected profitability of clearing declines with increases in the unit costs of low-skill labor, capital, transport and communications. Forest-sector outputs are traded internationally; dollar-denominated input costs decrease (and profitability increases) when the exchange rate increases. Governance has two anticipated effects in this context. Local government efficiency and integrity should increase the expected profitability of forest-sector production, which will in turn promote forest clearing. On the other hand, greater regulatory effectiveness may discourage forest clearing in protected areas, if local governments are actually concerned about clearing.

We posit effects for local structural factors as well. Higher population density should increase the demand for cleared land. Production will be more costly on more steeply-sloped land, and clearing will be more costly in areas (and months) with heavier precipitation.

6. Data

We have drawn the data for our estimation exercise from a variety of sources. All forest-clearing information for the period Dec. 2005 – Dec. 2010 comes from FORMA, which, as we have previously noted, provides indicators of large-scale forest-clearing at 1 km resolution for all forested areas in Indonesia. To index determinants of expected revenue, we use international market prices and world demand for hardwood sawlogs (our proxy for tropical wood products) and palm oil. We draw the price series from IMF data[10] and adjust to constant-dollar prices using the US GDP deflator[11]. Data on world palm oil production have been provided by the US Department of Agriculture[12], while world production statistics for sawlogs have been obtained from the FAO[13].

Among local input price variables, the only available time series is a proxy for communications cost. Our index is an estimate of mobile phone coverage that we construct from high-resolution data provided by GSM World, Inc.[14] In addition, we include three cross-sectional proxies: (1) An index of the economic opportunity cost of forested land developed by Resources for the Future and Climate Advisors (RFF 2011); (2) Estimated travel time to the nearest city of 50,000 or more people in the year 2000, from Nelson (2008). The travel time data are available at a high level of spatial resolution. For this exercise, we estimate kabupaten means, as well as standard deviations to control for within-kabupaten variation. (3) The average poverty rate in 2000, a proxy for the prevalence of low-skill, low-cost labor, obtained from the World Bank.

Our interest rate series is the one-month rate on notes issued by Bank Indonesia[15], adjusted for inflation using annual estimates from the World Bank[16]. We have drawn exchange rate data from OANDA's historical database[17]. Our land-use data are from a high-resolution digital map of Indonesia, as noted in Saxon and Sheppard (2010). All indices of governance quality have been drawn from the KPPOD survey database for Indonesia. Our precipitation data come from the PREC/L (PRECipitation REConstrucion over Land) database as described by Chen, et al. (2002). The terrain slope data are kabupaten averages from Verdin, et al. (2007). Since the underlying slope data are at higher resolution, we also calculate standard deviations to control for within-kabupaten variations.

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10. The relevant IMF data series are prices for Hard Logs, Best Quality Malaysian Meranti, import price Japan, US$ per cubic meter; and Palm Oil, Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, US$ per metric tonne. Source: IMF Primary Commodity Prices, available online at http://www.imf.org/external/np/res/commod/index.asp

11. Source: Bureau of Economic Analysis, Table 1.1.9. Implicit Price Deflator for Gross Domestic Product, available online at http://www.bea.gov/national/nipaweb/index.asp

12. US Department of Agriculture, Foreigh Agricultural Service. Available online at http://www.fas.usda.gov/psdonline/psdQuery.aspx

13. World production of sawlogs and veneer logs, available online at http://faostat.fao.org.

14. Mobile phone coverage is reported at frequent intervals; we interpolate to produce a full monthly dataset.

15. Source: Division of Economic & Monetary Data & Information Processing, Bank Indonesia, Table 1.25, Sertifikat Bank Indonesia, 1 Bulan. Available online at http://www.bi.go.id/web/en/Statistik/Statistik+Ekonomi+dan+Keuangan+Indonesia/Versi+HTML/Sektor+Moneter/

16. Source: World Development Indicators. Available online at http://databank.worldbank.org/ddp/home.do?Step=12&id=4&CNO=2

17. Source: OANDA, Historical Exchange Rates. Available online at http://www.oanda.com/currency/historical-rates

7. Econometric Specification

From the expected profitability equation (1), we specify our estimating equation as follows:
(2) $\log Clear_{it} = \beta_0 + \beta_1 \log(PalmPrice)_{it-i} + \beta_2 \log(LogPrice)_{it-j} + \beta_3 \log(PalmQuant)_{it-k} + \beta_4 \log(LogQuant)_{it-l} + \beta_5 \log(OppCost)_i + \beta_6 \log(PovRate)_i + \beta_7 \log(MobileCov)_i + \beta_8 \log(MeanTravT)_i + \beta_9 \log(sdTravT)_i + \beta_{10} (IntRate)_{t-m} + \beta_{11} \log(XRate)_{t-n} + \beta_{12} \log(InvGovQual)_I + \beta_{13} \log(RegQual)_I + \beta_{14} LogPct_i + \beta_{15} TimbPct_i + \beta_{16} PalmPct_i + \beta_{17} ProtPct_i + \beta_{18} \log(PopDens)_{it} + \beta_{19} \log(Precip)_{it-w} + \beta_{20} \log(MeanSlope)_I + \beta_{21} \log(sdSlope)_i + \beta_{22} \log(Forest2000) + \varepsilon_{it}$

where prior expectations on parameter signs are:[18]
$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_9, \beta_{11}, \beta_{12}, \beta_{14}, \beta_{15}, \beta_{16}, \beta_{18}, \beta_{21}, \beta_{22} > 0$
$\beta_8, \beta_{10}, \beta_{13}, \beta_{17}, \beta_{19}, \beta_{20} < 0$

Clear	=	FORMA forest-clearing index
PalmPrice	=	Constant-dollar palm oil futures price, lagged i months
LogPrice	=	Constant-dollar sawlog price, lagged j months
PalmQuant	=	World palm oil production, lagged k months
LogQuant	=	World sawlog production, lagged l months
OppCost	=	Agricultural opportunity cost
PovRate	=	Poverty rate
MobileCov	=	Coverage by mobile phone networks
MeanTravT	=	Mean travel time to nearest city of 50,000+
sdTravT	=	St. dev. travel time to nearest city of 50,000+
IntRate	=	Real interest rate, lagged m months
XRate	=	Rupiah/dollar exchange rate, lagged n months
InvGovQual	=	KPPOD index of governance quality for investors
RegQual	=	KPPOD index of regulatory quality
LogPct	=	% of area zoned for logging concessions as of 2005
TimbPct	=	% of area zoned for timber plantation concessions as of 2005
PalmPct	=	% of area zoned for palm oil plantation concessions as of 2005
ProtPct	=	% of area zoned for protection of natural forest
PopDens	=	Population Density
Precip	=	Precipitation, lagged w months
MeanSlope	=	Mean slope
sdSlope	=	St. dev. slope
Forest2000	=	Uncleared natural forest area in 2000
ε_{it}	=	Random error term with temporal and spatial components.

18 In the cases of TravT and Slope, we expect the standard deviation terms to modify the effects of the mean terms with opposite signs. In both cases the expected sign for the mean is negative, so the expected sign of the standard deviation is positive.

The model includes six short-term market variables: prices and quantities for palm oil and sawlogs, the interest rate and the exchange rate. We expect the standard investment calculus to produce a negative effect for the real interest rate. Palm oil and sawlogs are traded internationally; their expected profitability and associated forest-clearing should be positively associated with the rupiah/dollar exchange rate, because increases in that rate will lower the dollar cost of local inputs while leaving the dollar-denominated prices of exports unchanged. The expected prices and global demands for palm oil and sawlogs are positively associated with expected profitability, ceteris paribus, so they should be positively associated with forest clearing as well. We have no basis for a priori specification of appropriate lags for expectations-formation; they are quite likely to differ by variable. During the estimation process, we retain the single lagged value of each variable that provides the best fit. A priori, we would expect the palm oil price variable to have the shortest lag because our measure is the futures price.

While all six market variables, rainfall and mobile phone coverage are observed in time series, we have only single cross-sectional observations for the four other proxies for local input prices. We expect the agricultural opportunity cost of forested land and the poverty rate to be positively associated with forest clearing: the former because it provides a measure of conversion profitability, and the latter because it proxies the local availability of low-cost, low-skill labor for forest clearing. We acknowledge some ambiguity in the latter expectation, since some kinds of agricultural production on cleared land will require labor of the same type. We expect mobile phone coverage to be positively associated with forest clearing, because greater coverage lowers investor costs. Unit transport cost should be negatively associated with clearing, since palm oil and sawlogs are bulk commodities. In the same vein, we would expect travel time to the nearest port to be negatively associated with forest clearing. Although our indicator is the best available, it measures travel time to the nearest city of significant size, rather than time to the nearest port. In light of this difference, we remain agnostic about the potential size and significance of the measured effect.

Equation (2) includes a measure of governance quality for investors. Our database includes three relevant variables from the KPPOD survey: Quality of Assistance with Land Access; Capacity and Integrity of the Government; and Security and Conflict Resolution. A higher score on each variable should indicate a better environment for investment in forest-sector production. We would therefore expect a positive association between each variable and forest clearing. The other governance measure in (2), Regulatory Quality, may be negatively associated with forest clearing in local protected areas. This will occur if local governments treat forest protection as a regulatory issue on par with other forms of local regulation.

We incorporate five types of land use, measured as percents of total area in each kabupaten. We include four types in the regression, excluding areas that are not explicitly zoned for protection or commercial exploitation.[19] A priori, we would expect areas zoned for commercial production to have more forest clearing than protected areas.[20]

Our model includes population density, which is related to local settlement and demand for forest-sector products. A priori, we would expect this variable to be positively associated with forest clearing. Finally, our specification includes two local physical factors: monthly precipitation and terrain slope. Forest clearing is more costly when precipitation hinders burning, so we would expect a strong negative association between the two variables. We expect a very short lag, if any, in the impact of precipitation on forest clearing. Suitability for plantation production declines with terrain slope, so we would expect a negative association with this variable as well. Our kabuten-level measure of average terrain slope is calculated from highly-disaggregated spatial data, and kabupatens with the same average slope may have very different patterns of variation around the average. We capture this variation with the standard deviation, which we expect to moderate the measured effect of slope. If the marginal effect of mean slope is negative, as we expect, then we would expect the marginal effect of the standard deviation to be positive. In a similar vein, we have included the standard deviation of access time along with our measure of kabupaten mean access time.

8. Econometric Results

In this section, we present our estimation results for Indonesian islands that are significant forest clearing sites. We exclude Java and Bali, because they are heavily populated and largely cleared, and the islands of Nusa Tenggara that are not in the tropical forest zone**.**

8.1 Core Model Estimates: Major Geographic Divisions

Table 1 reports results for a core model that includes the variables in equation (2) that can be used for panel estimation by fixed effects. The first two columns of Table 1 present fixed and random effects estimates for all kabupatens in the tropical forest areas of Indonesia. Random effects estimation is preferable because it is more efficient, but its use depends on failure of the appropriate Hausman test to reject the null hypothesis of equal parameters in random and fixed effects estimation. Failure occurs in this case ($\chi2$ =2.74, p=.9494), so we adopt the random effects estimator. We retain this estimator for the remainder of the work reported in the paper.

As the strong Hausman results indicate, columns (1) and (2) have effectively-identical parameter estimates. In both equations, all estimated parameters have the expected signs and high levels of significance. Rainfall affects forest clearing with a short lag (one month

19. We exclude one land use type to prevent perfect collinearity with the regression constant.

20. Indonesian areas identified as "protected" may vary substantially in the actual degree of protection, lending some uncertainty to the assessed effectiveness of protection. We have no information on the relative allocation of monitoring and enforcement resources to different protected areas,.

provides the best fit). Our results indicate that both expected prices and demands have strong effects on forest-clearing, with substantially higher elasticities for the quantity effects. Our final estimates use the lags that provide the best fit to the data. As expected, we find no lag for the palm oil futures price, since it already incorporates expectations. Our best result for the sawlog price suggests that a lag of about nine months characterizes the process of price expectation revision and translation of revised expectations into forest clearing. The results for palm oil and sawlog demands suggest lags of 15 and 12 months, respectively, before market changes induce changes in forest clearing. Changes in the real interest rate take significantly longer to induce changes in forest clearing: 23 months, in our best estimate. The response to changes in the real exchange rate is faster. We find approximately equal effects for lags of 9, 10 and 11 months, so we use the three-month average. We lag mobile phone coverage by one year to guard against simultaneity (a contemporaneous effect could easily reflect two-way causation). As Table 1 shows, the lagged variable is highly significant.

Columns (3) – (7) report random effects estimates for five islands and island groups: Sumatra, Kalimantan, Sulawesi, Maluku and Irian Jaya. Sample sizes vary from 3,969 observations for Sumatra to 294 for Maluku. In light of this variation, it would not be surprising to see substantial variation in estimation results. However, the quality of the results is quite similar. The estimated impact of rainfall has the expected sign in all cases and statistical significance in 3 cases. Product price elasticities have the expected signs in 8 of 10 cases and are statistically significant in 6 cases. Quantify effects have the expected signs in all cases, and statistical significance in 7 of 10 cases. The real interest rate has the expected sign in all five cases, although it has statistical significance in only two (Kalimantan and Sulawesi). The exchange rate is statistically significant in 3 of 5 cases and has the expected sign in all cases.

Table 1: Economic Dynamics and Forest Clearing

All Variables in Logs Except Month and Real Interest Rate
Lags (Months) in Brackets

Dependent Variable: Log(Forest Clearing Index)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	Sumatra	Kalimantan	Sulawesi	Maluku	Irian Jaya
Estimator	FE	RE	RE	RE	RE	RE	RE
Rainfall[-1]	-0.381	-0.379	-0.557	-0.308	-0.085	-0.407	-0.152
	(10.19)**	(10.14)**	(9.42)**	(3.92)**	(1.13)	(2.62)**	(0.92)
Palm Oil	0.816	0.815	0.385	1.716	0.898	0.270	0.688
Futures Price	(10.71)**	(10.70)**	(3.40)**	(11.22)**	(4.53)**	(0.59)	(3.51)**
Sawlog	1.134	1.129	1.562	2.438	-1.316	-2.809	1.209
Price [-9]	(2.97)**	(2.96)**	(2.76)**	(3.12)**	(1.32)	(1.23)	(1.24)
Global Palm	5.225	5.231	6.346	5.808	3.959	13.842	-0.740
Oil Prod.[-15]	(6.53)**	(6.53)**	(5.35)**	(3.60)**	(1.90)	(2.89)**	(0.36)
Global Sawlog	14.651	14.594	12.376	22.205	10.448	28.808	7.541
Prod.[-12]	(9.27)**	(9.24)**	(5.12)**	(7.04)**	(2.56)*	(3.11)**	(1.89)
Real Interest	-0.044	-0.044	-0.018	-0.105	-0.052	-0.046	-0.031
Rate [-23]	(7.03)**	(7.07)**	(1.96)	(8.37)**	(3.19)**	(1.24)	(1.93)
Exchange Rate	2.827	2.823	1.246	3.881	4.961	9.025	2.813
[-9,10,11]	(4.94)**	(4.93)**	(1.47)	(3.33)**	(3.30)**	(2.63)**	(1.93)
Mobile Phone	0.117	0.112	0.095	0.115	-0.511	-4.106	0.008
Coverage [-12]	(7.09)**	(6.98)**	(4.77)**	(0.96)	(2.81)**	(3.15)**	(0.06)
Constant	-395.992	-394.855	-344.594	-579.689	-307.770	-854.422	-189.797
	(9.15)**	(9.13)**	(5.26)**	(6.69)**	(2.74)**	(3.34)**	(1.73)
Observations	8673	8673	3969	1960	1225	294	1225
Kabupatens	177	177	81	40	25	6	25

Hausman Test for Fixed Effects (1) vs. Random Effects (2):

X^2 2.74 (p=0.9494)

Absolute value of t statistics in parentheses
Significance: * .001; ** .01; * .05**

8.2 Estimation of the Fully-Specified Model

Consistent, efficient panel estimation techniques permit inclusion of cross-sectional variables that may influence average levels of deforestation in Indonesian kabupatens. We have included several of these variables in the full specification in equation (2). Table 2 reports results obtained from the random effects estimator programmed in Stata (column (1)), as well as three alternative estimators programmed in R (columns (2) - (4)). We include the latter because appropriate adjustments for spatial dependence are not yet available in Stata. Column (2) reports estimation results equivalent to those in (1), obtained using the method of Swami and Arora (1972) for a fully-balanced panel. [21] Column (3) reports estimates from the method of Kapoor, et al. (2007), which adjusts for spatial autocorrelation across kabupatens. Column (4) reports estimates from the method of Millos and Paris (2009), which adjusts for both spatial autocorrelation and spatial lags across kabupatens. We provide a brief introduction to the three estimators in the appendix to this paper.

Inspection of Table 2 reveals remarkable similarity in the results obtained by all of our estimators: Signs and general significance levels are identical for 81 estimates and different for only 3. We assign particular importance to column (4), which reports high significance for both spatial autocorrelation (ϱ) and spatial lags (λ), and adjusts for both error components. All variables in the KPPOD governance survey are insignificant in every case, so we have excluded them from the table.

In Table 2, our results for core-model time series variables are very similar to those reported in Table 1. Signs and elevated significance levels match throughout, as do estimated parameter sizes (except for the rainfall results in the R-based estimates). Table 2 includes the cross-section variables in equation (2): uncleared forest in 2000; terrain slope (mean and SD); land opportunity cost, population density; the poverty rate; and access time to the nearest city (mean and SD). We also include information on zoning status: the % of area in each kabupaten zoned for forest protection, palm oil plantations, timber plantations and logging concessions. Among the cross-sectional variables, only three are highly significant and have the expected signs in all four estimates: uncleared forest in 2000; mean slope (modified by its standard deviation[22]); and % area designated for palm oil plantations. Zoning for logging concessions is also consistently-signed, with a high significance level in two of four cases. The large, positive, significant results for palm oil plantations and the insignificance of protected-area status are notable in all four estimates.

21. Implementation in R requires a fully-balanced panel, which we produce by spatial interpolation of available monthly rainfall observations to replace missing observations in some kabupatens. The result is an enlarged panel (193 kabupatens) relative to the dataset used for our Stata estimate in column (1) (142 kabupatens).

22. The result for the standard deviation (SD) indicates that slope effects are more pronounced in areas with relatively small variations in slope.

9. Summary and Conclusions

In this paper, we have employed a large panel database to investigate the determinants of forest clearing in Indonesian kabupatens since 2005. Using monthly forest clearing data from FORMA (Forest Monitoring for Action), the paper provides the first Indonesian impact assessment for short-run economic variables, as well as impact estimators for indicators of area zoning, forest protection, the opportunity cost of forested land, the availability of communications infrastructure, and the quality of local governance. In addition, we test the effects of variables that have been included in more traditional analyses of forest clearing: rainfall, terrain characteristics, the poverty rate, population density and transport cost.

Our results strikingly demonstrate the importance of economic factors in the dynamics of forest clearing. In our full estimation model, significant roles are played by short-run changes in several economic variables, as well as communications infrastructure, zoning for palm oil plantations, and three physical factors – uncleared forest in 2000, rainfall and terrain slope. In counterpoint, many cross-section variables prove to be insignificant: local governance quality, a direct estimate of land opportunity cost (RFF, 2011), access time, population density, the poverty rate, protected-area status, and zoning for timber plantations.

We believe that the most distinctive feature of our approach is its inclusion of short-run economic variables, which was simply not possible before the advent of FORMA. As we have noted in the paper, economic theory has long posited critical roles for expected forest product prices, quantity demands, interest rates and exchange rates in the investor calculations that lead to large-scale clearing for commercial production. The econometric analysis reported in this paper introduces all of these variables and explores the time lags that characterize their impact on forest clearing. We find highly-variable lags: less than a year for product prices; around one year for product demands and the exchange rate; and closer to two years for the real interest rate. All variables are highly significant in our panel analysis, and their fluctuations, along with variations in rainfall, explain a major portion of the changes in Indonesian forest clearing that are strikingly visible in Figure 1.

From a policy perspective, our results highlight the importance of incorporating economic dynamics into arrangements that offer financial compensation for forest conservation. Our findings are strongly consistent with a model of forest clearing as an investment that is highly sensitive to expectations about future forest product prices and demands, as well as changes in the cost of capital (indexed by the real interest rate), the relative cost of local inputs (indexed by the exchange rate), and the cost of land clearing (indexed by local precipitation). By implication, the opportunity cost of forested land fluctuates widely as changes occur in international markets, local weather conditions, and decisions by Indonesia's financial authorities about the exchange and interest rates.

Our results cast doubt on the effectiveness of traditional protection arrangements, which prove to be insignificant in all of our estimates. But they are also cautionary for compensation-based approaches, since they suggest that the perceived opportunity cost of forested land varies widely over time, and in response to numerous dynamic factors. By implication, it may prove very difficult to negotiate fixed compensation schemes for forest conservation, area-by-area. We confront this difficulty in Hammer, et al. (2011) and propose a tractable scheme based on changes in national forest conservation performance over time. Our proposed system focuses solely on incentive payments to national governments, leaving them free to make flexible arrangements with local forest proprietors.

Table 2: Introduction of Cross-Sectional Variables

Variables Logs Except Interest Rate, Area %'s Lags (Months) in Brackets

Dependent Variable: Log(Forest Clearing Index)

	(1)	(2)	(3)	(4)
Rainfall [-1]	-0.366	-0.004	-0.003	-0.002
	(9.08)**	(6.842)***	(5.242)***	(4.993)***
Palm Oil Futures Price	0.904	0.784	0.782	0.356
	(10.67)**	(11.347)***	(8.520)***	(7.669)***
Sawlog Price [-9]	1.342	1.354	1.343	0.593
	(3.15)**	(3.984)***	(2.981)**	(2.595**
Global Palm Oil Production [-15]	5.811	4.636	4.458	2.000
	(6.53)**	(6.398)***	(4.636)***	(4.109)***
Global Sawlog Production [-12]	15.013	12.140	11.987	5.440
	(8.50)**	(8.854)***	(6.613)***	(5.880)***
Real Interest Rate [-23]	-0.054	-0.048	-0.046	-0.020
	(7.75)**	(8.407)***	(6.088)***	(5.201)***
Exchange Rate [-9,10,11]	2.544	2.675	2.605	1.190
	(3.99)**	(5.225)***	(3.836)***	(3.458)***
Mobile Phone Coverage [-12]	0.073	0.062	0.083	0.045
	(4.37)**	(4.174)***	(5.092)***	(3.772)***
Uncleared Forest (2000)	1.525	1.207	1.110	0.958
	(7.40)**	(7.371)***	(6.652)***	(6.690)***
Mean Slope	-2.783	-2.459	-2.513	-1.674
	(5.98)**	(6.497)***	(6.340)***	(5.124)***
St. Dev. Slope	1.535	0.965	1.090	0.929
	(3.46)**	(2.879)**	(3.251)**	(3.028)**
Land Opportunity Cost	0.133	-0.061	-0.058	0.097
	(0.65)	(0.417)	(0.376)	(0.786)
Protected Area %	-0.117	0.398	0.390	-0.147
	(0.10)	(0.380)	(0.378)	(0.153)
Timber Plantation Area %	0.696	0.033	-0.253	-2.266
	(0.36)	(0.018)	(0.139)	(1.275)
Logging Concession Area %	-4.292	-1.920	-1.288	-3.156
	(2.71)**	(1.402)	(0.951)	(2.483)*
Palm Oil Plantation %	16.361	16.438	15.056	13.787
	(4.95)**	(5.234)***	(4.734)***	(4.871)***
Population Density	0.128	-0.067	-0.158	-0.071
	(0.46)	(0.299)	(0.706)	(0.342)
Poverty rate (2000)	1.761	1.183	1.137	0.302
	(0.80)	(0.652)	(0.591)	(0.199)
Access Time to Nearest City (50,000+)	1.543	0.008	0.102	0.046
	(2.46)*	(0.020)	(0.235)	(0.118)
St. Dev. Access Time	-1.081	-0.016	-0.086	-0.195
	(1.83)	(0.038)	(0.209)	(0.512)
Constant	-417.412	-337.874	-331.540	-152.641
	(8.61)**	(8.882)***	(6.590)***	(5.944)***
ϱ			.257	.411
				(9.41)***
λ				.538
				(20.933)***
Adj. R^2	.556	.130	.827	.405
Kabupatens	142	193	193	193

Absolute value of t statistics in parentheses
Significance: ***.001; ** .01; * .05

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Appendix: Estimation of Spatial Models

Columns (2) – (4) of Table 2 report results from a succession of panel estimators implemented in R. Estimation requires a complete, balanced panel, so we have used spatial interpolation to replace some missing monthly rainfall observations in our kabupaten-level dataset. The estimation panel includes five years of monthly data (Jan. 2006 – Dec. 2010) for 193 kabupatens, yielding 11,580 observations. We construct a weighting matrix from the GIS shapefile for the 193 kabupatens, defining neighbors to be kabupatens with borders that are within 0.5 arcdegrees (roughly 50 kilometers) of each other. The weighting matrix W is row-standardized, so that each row sums to 1. Table A1 displays the frequency distribution of connections (or links) between kabupatens.

Table A1: Frequency Distribution of Kabupaten Links

Links	1	2	3	4	5	6	7	8	9	10
Freq.	5	7	6	16	11	18	16	23	17	13

Links	11	12	13	14	15	16	17	18	19
Freq.	12	25	10	6	2	2	1	1	2

Our objective is to efficiently and consistently estimate the following model:

(1) $y = \alpha + X\beta + u$,

where y is a panel of logs of forest clearing activity (by kabupaten and month), X is a panel of explanatory variables and u is an error term. OLS estimates of model parameters are not efficient or consistent if u is subject to serial or spatial autocorrelation. Standard panel estimation employs the model:

(2) $y = \alpha + X\beta + \mu + E$,

where the error component μ is specific to panel groups and E is assumed to be uncorrelated with μ and the regressors in X. Estimation of (2) via GLS will produce efficient results for non-autocorrelated data. We report estimates obtained by the method of Swami and Arora (1972) in column (2) of Table 2.

For forest clearing analysis, standard GLS estimation may be insufficient because of spatial dependence. As Figures 2 and 3 indicate, forest clearing clusters frequently cross kabupaten boundaries. Kapoor, et al. (2007) propose the following model for the case where error terms are correlated across spatial units:

(3) $y = \alpha + X\beta + u$,

where u follows a first-order spatial autoregressive process,

(4) $u = \varrho(I_T \otimes W)u + E$

and observations are stacked by time period rather than panel group. This model can be interpreted as a time series of kabupaten cross sections, and ϱ is the coefficient of spatial spillover of the errors. To allow for temporal autocorrelation, E is specified as:

(5) $E = (e_T \otimes I_N)\mu + \nu$

where μ is a vector of kabupaten-specific error components, e_T is an appropriately-dimensioned unit vector, and v contains idiosyncratic error components that vary over time and space. We report the results of estimation by this model in column (3) of Table 2.

Dynamic economic factors propel growing forest-clearing clusters across kabupaten boundaries. It is therefore likely that our panel data are also characterized by spatial lags, in which clearing in one kabupaten is related to clearing in neighboring kabupatens. Following Millo and Piras (2009), we specify and estimate a model with general spatial autocorrelation:

(6) $y = \lambda Wy + X\beta + u = \varrho Wu + \eta$,

$u = \varrho Wu + \eta$

where $\eta \sim N(0, \boldsymbol{\Omega})$, $\boldsymbol{\Omega} \neq \sigma^2 I$. This specification incorporates both a pure spatial error model when $\lambda = 0$, and a pure spatial lag model when $\varrho = 0$. We report our results in column (4) of Table 2.