Cattle in the Woods:

Impact of Beef Prices on Deforestation in the Amazon

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Abstract

Tropical deforestation is a pressing environmental issue. I study how changes in global beef demand drive deforestation in Brazil, where forests are being converted to pasture in order to carry larger herds of beef cattle. Using data on municipal-level deforestation rates and a transportation cost-based measure of local returns to beef, I document a negative correlation between returns to beef and deforestation rates. I show that this can be rationalized by a dynamic model of a profit-maximizing rancher, who chooses deforestation to create new pasture as well as the size of cattle herd. Temporary increases in returns to beef optimally lead to increased slaughter, thereby reducing herd size and the contemporaneous demand for deforestation. However, following a permanent increase in returns, the rancher optimally accumulates a bigger herd, which may necessitate more deforestation. Using an Euler-equation GMM approach, I estimate the parameters of this model and simulate future deforestation under alternative return scenarios. Based on these counterfactuals, I confirm the divergence between responses to permanent and temporary shocks. My estimates imply that deforestation is inelastic to beef prices, with a central estimate of a 10% permanent increase in returns to beef leading to a 0.026 percentage point increase in average annual long-run deforestation rate.

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1 Introduction

Tropical rainforests are storehouses of global carbon and biodiversity. However, in recent years, they have come under deforestation pressure from agriculture, logging, and cattle ranching. Reducing tropical deforestation rates is an important part of the portfolio of Nature-Based Solutions (NBS) to combat climate change (Griscom et al. 2019). In Brazil, the world's largest exporter of beef, deforestation in the Amazon rainforest (and the neighboring Savanna, known as the Cerrado) has been driven by clearing forests to create more pasture. Concerns that growing global demand for beef, especially from middle-income countries including China and East-Asian nations, will drive up the rate of forest clearing (Godfray et al. 2018) have elicited calls from environmental groups for reducing meat, especially beef, consumption as well as for greater monitoring and transparency of agricultural supply chains. These "demand-side" policy interventions attempt to reduce the payoff from raising cattle on deforested lands, thereby reducing incentives for deforestation. Deforestation, and associated policy interventions, represent an important *climate risk factor*, especially stakeholders in global agricultural supply chains. As such, this pasture-driven deforestation arises through changes in the global price of beef, as production decisions of ranchers depend on the price signal. Therefore, the validity of this channel as well as the efficacy of demand-led anti-deforestation interventions, such as the ones mentioned above, rest on how deforestation responds to changes in beef prices. In this paper, I provide estimates of the response of deforestation rates in tropical Brazil to changes in beef demand, as captured by exogenous price variation, using a representative-agent forward-looking rational-expectations framework.

Removal of Amazon rainforest[1] for pasture is inherently dynamic in two ways. First, *primary* deforestation is irreversible, at least in the medium run - pasture never reverts to natural *old-growth* forest. Because of this irreversibility, while the cost of deforestation is borne at the time of clearing, the benefits can accrue for several periods in the future. Second, the demand for pasture and, hence, demand for deforestation is derived from beef supply considerations, which, in turn, must account for the biological (reproductive) dynamics of beef cattle. These dynamics imply that there might be a difference in short-run and long-run responses, as well as responses to temporary and permanent shocks.

Therefore, I use a dynamic decision framework to address my research question. I model the

[1] My sample consists of municipalities in both the Amazon, which is a tropical rainforest, as well as the neighboring Cerrado, which is a savannah grassland. While these are distinct biomes, I use the shorthand Amazon to refer to both of them.

incentives of a *forward-looking* rancher who jointly chooses the size (or, equivalently, the fraction to slaughter) of his cattle herd as well as new pasture creation via deforestation. The model implies a structural relationship, mediated by choice of the size of the cattle herd, between exogenous beef prices and deforestation rates. I use panel data on prices and deforestation rates for a sample of Amazonian municipalities to estimate structural parameters associated with deforestation costs. Given these estimated parameters, I simulate the model to make quantitative inferences about the contemporaneous and long-run response of deforestation to temporary and permanent price shocks.

First, I theoretically model how returns to beef affect the choice of deforestation. Deforestation is driven by the need to create more pasture in order to carry larger herds of cattle. A bigger herd allows for a larger slaughter offtake leading to higher revenue. The tradeoff involved in generating higher revenues today by slaughtering more cows arises because cattle is both a consumption as well as a capital good - the slaughter (or "consumption") decision today affects the size of the herd available for slaughter tomorrow, as well as in future periods. More slaughter today reduces future herd size directly, as the number of standing adult cows goes down, as well as through reproduction, as fewer breeding adults are now available to give birth to new calves. Moreover, as it takes time for calves to reach slaughter and breeding age, the rancher must also account for lag effects in herd dynamics. The costs of the rancher's operations arise from need to feed the herd. Available pasture is a soft capacity constraint on the size of the herd - in my model, the rancher incurs a cost (or revenue losses) if herd size exceeds the carrying capacity of available pasture.

The rancher can deforest existing rainforest to increase his stock of carrying capacity. Deforestation in the Amazon is typically carried out by slash-and-burn methods and is, therefore, costly. Inputs needed for deforestation, such as labor or machinery, are typically locally sourced and input costs are likely to reflect local scarcity. I account for this in my model by allowing for increasing marginal cost of deforestation for the representative rancher.

In the model, an infinitely-lived rancher optimally decides *each period* how much of the herd to slaughter and deforestation to undertake in order to maximize his lifetime discounted profits. This rancher is a price-taker and takes the stochastic process of beef prices (which I restrict to be first-order Markov) as given. The optimal choice of herd size is essentially a consumption-saving decision: the revenue lost from the marginal cow saved balance the expected revenue from selling this cow and its progeny in the future, net of pasture-related costs (Jarvis 1974). Similarly, the optimal deforestation each period must be such that the cost of deforesting the marginal unit of land today is balanced by the pasture-related benefits that will accrue from that unit in the future. Importantly, these future benefits not only include the relaxed capacity constraint for the next period but also for all subsequent periods, as deforestation is irreversible. In the presence of increasing marginal costs of deforestation, the rancher has a cost-smoothing incentive given uncertain future returns to pasture.

The model highlights that a rancher's optimal response to an increase in price is qualitatively different depending on whether the increase is perceived to be temporary or permanent. A temporary price increase prompts the rancher to slaughter a larger portion of his herd, which in turn reduces the need for deforestation in subsequent periods, until the herd recovers and more pasture is needed. A permanent price increase, on the other hand, leads the rancher to grow his herd so as to allow for higher offtake for slaughter every period. To do so, the rancher must temporarily reduce slaughter. As the herd size grows, it necessitates a higher pasture requirement, thereby increasing the deforestation rate.

I assemble panel data on deforestation rates and returns to beef for a sample of 533 Brazilian municipalities that lie in the part of Amazon that has come to be known as the 'arc of deforestation'. Data span a period of 11 years - from 2001 to 2011. The deforestation rates are calculated using publicly available rasters from the MAPBIOMAS project that uses satellite imagery to create landcover maps for Brazil. Local beef prices are constructed as an aggregate price level minus the lowest transportation cost to a port that exports beef. These costs are based on a model of transportation costs, which allows for time-series as well as cross-sectional variation.

I document two empirical facts. First, that deforestation rates are negatively (or, depending on specification, very weakly positively) associated with local beef prices, even after accounting for municipality and time fixed effects. This seemingly counter-intuitive result is not surprising in the light of the model, which suggests that a price increase, to the extent it is perceived to be short-lived, reduces deforestation rates. Second, I find that this negative correlation becomes positive at a lag of three years. Interestingly, this 3-year lag structure resembles the 3-year long growth cycle of the average cow in the Amazon.

A solely data-based approach that correlates exogenous variation in returns to beef to deforestation rates has two main limitations for measuring long-run elasticity. First, as stated above, deforestation decisions respond dramatically differently to changes in returns, depending on whether these changes are perceived to be temporary or long-lasting. It is difficult to directly infer this nature of shocks in short panels, without making additional assumptions. Second, when making long-run forecasts, we need to be clear about what aspects of the economic and policy environment are held fixed. The model also demonstrates that the permanent component of the returns process is a key component of this environment. The deforestation "policy function" that can be directly estimated from the data is not invariant to changes in the permanent component of the returns process.

Therefore, I adopt a structural approach and use the model as an empirical framework. First, I estimate parameters associated with the land clearing cost. Relatedly, I calibrate (based on other studies) agronomic parameters associated with cattle reproduction and feed requirements. Next, holding these parameters fixed, I simulate deforestation paths optimal for the representative rancher under alternative return scenarios.

To identify parameters of the structural model, I use the first-order optimality conditions and the rational-expectations hypothesis (Hall 1978). Under these restrictions, the model implies orthogonality moment conditions that can be exploited in a Generalized Method of Moments (GMM) framework to estimate the parameters. The rational expectations hypothesis imposes that rancher's subjective beliefs about beef prices in the model are consistent with the "true" data-generating process. The orthogonality moment conditions follow from the fact that at a given point in time, any deviations between the data and the model must be due to unanticipated "innovations", which are, by construction, uncorrelated with the information available to the rancher at that time. This approach is similar to the Euler equation approach used to estimate consumption-based CAPM models (Hansen and Singleton 1982).

Next, I simulate the model to generate counterfactuals under alternative price processes. Having estimated deforestation cost parameters, and calibrated the agronomic ones, the only parameters that need to be estimated are those of the beef price process. I use an AR(1) in logs specification for this process. Note that the cost parameters are estimated independently of the shock process - misspecification of this process does not impact cost estimates, only the counterfactuals.

Based on my estimates, I find that the deforestation indeed goes down as result of a temporary increase in beef prices. As expected, given the empirical facts documented earlier, this response is relatively small. The response of deforestation to a permanent increase in prices is positive. The contemporaneous response for both shocks is similar in magnitude (though in opposite directions). However, the long-run response to a permanent price change is surprisingly small. For my preferred estimate, I find that for permanent 10% increase in prices, contemporaneous deforestation increases by 0.023 percentage points. The average long-run deforestation rate increases by a similar magnitude - in other words, this increase persists until the forest is completely depleted.

The implication of these results is twofold. First, the concerns about indirect land use change, in this particular context, might be overstated. Second, given the relatively inelastic response of deforestation, policy interventions that target beef prices might not prove very effective. As I discuss later, these are strong claims that must be understood with certain caveats as I discuss. Nonetheless, as permanent price changes lead to persistent effects, there is scope to explore the complementarity between price-based and command-and-control policies.

The paper is organized as follows. Section 2 places the paper in context of the literature. Section 3 discusses the Amazon context and provides an overview of the data, including the key descriptive patterns mentioned above. Section 4 lays out the theoretical framework. Section 5 discusses how this framework can be used for estimation and discusses the estimation strategy. It also discusses the measures used for quantifying the deforestation response. Section 6 presents the results and discusses their implications, and Section 7 concludes.

2 Related literature

This paper examines deforestation by incorporating the supply decisions of producers of beef cattle, the commodity that drives deforestation. Deforestation rates depend on the equilibrium prices and quantities in the market for beef, which is the final output. My estimates can be used to map this final output market equilibrium to deforestation. As such, the crop (or pasture) acreage response to commodity prices - also known as *landuse elasticity* - is an important parameter in evaluating the impact of any policy that changes relative returns to alternative land uses. Hence, it is also a parameter in calibrating policy planning models, such as GTAP (used by the California Air Resources Board) and FAPRI (used by the Environmental Protection Agency). These models provide admissible evidence used to inform agri-environmental policies. For example, biofuel mandates, which are seemingly pro-environmental policies, have raised similar concerns of indirect landuse change - that increasing demand for biofuels might lead to higher rate of forest-to-crop conversion (Searchinger et al. 2008; Fargione et al. 2008). The conclusions from these models crucially depend on the magnitude of landuse elasticity (Barr et al. 2011; Ahmed, Hertel, and Lubowski 2009). Yet, there is considerable debate in the literature regarding the measurement and magnitude of these elasticities (Berry 2011; Babcock 2015). In this context, my paper provides estimates that provide useful information to calibrate these models.[2]

[2]The GTAP model uses the U.S. elasticity to calibrate its elasticity of land transformation, even for Brazil. In the GTAP model, this implied acreage elasticity, defined as percentage change in cropland acreage divided by percentage

My work contributes to econometric studies of land cover change. Among these, closely related to my research, Souza-Rodrigues (2019) uses a *static* discrete choice setup to quantify farmers' responses to permanent changes in prices. The paper uses cross-sectional variation in deforested *area* and returns to alternative land uses, the latter based on a transportation cost model. In contrast, I use a *dynamic* model, along with panel data on deforestation *rates* and returns to beef. Like Souza-Rodrigues (2019), I too use transportation costs to generate variation in returns to beef. However, in my data, these transportation costs vary over time within a municipality. Therefore, I adopt an approach similar to Lubowski (2002) and Lubowski, Plantinga, and Stavins (2006) and Scott (2014) that use panel data on landcover and, importantly, observed returns to alternative land uses to back out switching costs, under alternative behavioral models.[3] My framework is closer to Scott (2014) rather than Lubowski (2002) in that the latter takes a net-present value approach, while I incorporate forward looking dynamics. While these approaches can account for state-dependence (via past choices) as well as serially correlated unobservables, they do not allow for the transition rule of these unobservables to be endogenous. In my case, returns to deforestation depend not just on beef price and stock of available pasture, which are observed, but also on the herd size, which is an unobserved choice variable. To address this issue, I explicitly model the optimal choice of herd size and use the first order condition from this problem to correct for the unobserved state dynamics. [4]

The difference between short and long-run price responses of cattle supply decisions was first noted by Jarvis (1974). This insight was used by Rosen (1987) and Rosen, Murphy, and Scheinkman (1994) along with the time-to-build feature of cattle dynamics to explain the cyclicality in the historical time series of US cattle stocks. I use a similar framework, with the addition of capacity choice via deforestation. Subsequent papers in the "cattle cycles" literature, such as Aadland (2004), have used an Euler equation GMM approach to estimate parameters of the cattle cycle model using data on cattle stocks. Again, my paper uses a similar approach but instead of using data on cattle stocks, I use the model implied mapping between cattle choices with deforestation choices to use data on deforestation to infer deforestation cost parameters.

change in expected crop prices, is 0.05. For the FAPRI model, which uses a separate module for Brazil, this value is 0.13. See Barr et al. (2011) and the references therein.

[3]These studies belong to a larger literature that use structural econometric approaches to studying land use decisions. Early examples of this approach include Stavins (1999) and Chomitz and Gray (1996).

[4]This approach is similar in spirit to De Groote (2020), where it is used to account for unobserved effort choice in analyzing education choices, as well as by Van den Berg and Klaauw (2019) to account for job search effort in a labor search model.

My work also relates to a large number of studies that investigate deforestation in the Amazon[5] and other other tropical forests - see Wunder et al. (2020) and Börner et al. (2020) for reviews. Many of these studies, including Assunção, Gandour, Rocha, et al. (2015) and Harding, Herzberg, and Kuralbayeva (2020), use reduced-form panel data methods to infer how global commodity price fluctuations drive deforestation. My paper complements these studies and provides a way to structurally interpret their results. In particular, I clarify the nature of biases that might arise when using short run variation to infer long-run responses - a reduced form approach would require accounting for forward looking behavior and irreversibility of deforestation. This exercise is similar to Lemoine (2018), which sets up a dynamic decision problem to derives implications for climate econometrics i.e. what can be learned about responses to climate (a long-run unobservable average) using variation in weather (short run shocks around that average). By highlighting the divergence between responses to temporary and permanent changes, my work also suggests a possible rationale for why similar policies, based on their perceived persistence, have different effects as documented by a large number of impact evaluation studies.

Finally, my paper relates to the literature on structural model of storable commodities used to explain commodity price volatility (Deaton and Laroque 1992; Pirrong 2011). These are equilibrium models of inventory behavior of producers that describe how storage costs and output price uncertainty jointly determine production decisions. Roberts and Schlenker (2013) use this framework to estimate supply and demand elasticities for agricultural commodities. The deforestation costs in my model are similar to the convex storage costs in these models. While I do not study equilibrium in the output market, I microfound the storage costs to derive implications about the input choices and production.

3 Data

3.1 Context

The Amazon rainforest covers much of Northern and Western Brazil. Along with the adjacent tropical savanna, known as the Cerrado, it is one of the world's most biodiverse regions, as well a large terrestrial carbon sink. In this paper, "Amazon" refers to *Legal Amazon*, which is an

[5]These studies consider effects of various policies instituted to reduce deforestation as well as different institutional features that might drive deforestation. See Assunção and Rocha (2019), Assunção et al. (2019), Burgess, Costa, and Olken (2018), Cisneros, Zhou, and Börner (2015), Gibbs et al. (2015), Wong et al. (2019), Heilmayr et al. (2020), and Koch et al. (2019) and references therein.

administrative region covering the biomes of the Amazon rainforest and (part of the) Cerrado. While these biomes are geophysically and ecologically distinct, the entire region has come under immense deforestation pressure, much of it driven by pasture-related forest clearing.

Brazil is the world's largest exporter of beef, with roughly a quarter of the country's beef production coming from the Amazon. The Brazilian cattle boom started in the 1990s, with the impetus coming from export growth, which was driven by changes in exchange rate as well eradication of the Foot and Mouth disease. The cattle industry, which was historically based in the south of Brazil, started moving north, seeking out cheaper grazing land. The availability of cheaper land, relative to other forms of cattle feed, created a system of low-productivity extensive ranching, which persists to this day (Bowman et al. 2012). Ranches typically raise cattle for their entire lifecycle, from calving through the fattening stage. These cattle are then sold as beef[6] to slaughterhouses, which are either owned by or sell to large meatpackers that export the beef to Brazilian supermarkets and international markets (Vale et al. 2019).

Low productivity ranching implies very low cattle stocking rates - as low as less than one adult cow per hectare - thereby requiring large tracts of pasture. As cattle ranching has moved into the Amazon, so has forest clearing. Most deforestation has occurred along the agricultural frontier, which forms the south-estern boundary of the Amazon and has come to be known as the 'arc of deforestation'. As ranching and agriculture expands, the boundary moves further into the forest.

Deforestation rates rose into early 2000s, peaked in 2004 and have fallen since.[7] A part of the slowdown can be attributed to set of set of national policies implemented by the Brazilian government in 2004, and then again in 2008. Historically, all private properties in the Amazon are required to have 80% of their land under forests (Soares-Filho et al. 2014) but implementing this rule had been difficult. The new policy sought to enforce these restrictions using punitive measures, supported by improved satellite-based monitoring (Assunção, Gandour, and Rocha 2013; Nepstad et al. 2014). Despite several successes, enforcing these policies has still been difficult, primarily due to the vast extent and remote nature of the Amazon.

Four features of beef production in Brazil are most relevant to my analysis. First, the main input into beef production, besides cattle itself, is pasture. The cost of pasture creation, or clearing forests, forms a major component of production costs.

Second, individual cattle ranchers are small relative to the market and can be regarded as price

[6] Most Amazonian cattle are raised for beef. Milk is not an important product in these areas.

[7] They stayed low into the 2010s but have been on the rise again in the last two years, arguably due to the new government that strongly supports agricultural interests.

takers. While land tenure in the Amazon is contentious (Aldrich et al. 2012) [8], forests are cleared, usually through slash-and-burn, on both private as well as public land in order to create more pasture. Therefore, ranches are quite similar in how they operate and grow.

Third, given the uniformity in production technology, access to transportation infrastructure is a main determinant of variations profitability across ranches. Less accessible areas incur bigger transportation costs and receive a lower effective price for their output. A long literature has established roads as an important proximate cause of tropical deforestation, including in the Amazon (Pfaff et al. 2009). Reduced transportation costs due to better roads increase returns from agriculture and ranching, which creates incentives for deforestation. Moreover, to the extent higher commodity prices lead to higher deforestation rates, areas that are more accessible to markets face higher deforestation pressures (Angelsen 2007).

Fourth, while pasture is not the only land use in the Amazon and a substantial share of deforested land is under soy cultivation, pasture is the dominant driver of primary deforestation. As shown in the appendix (Figure A.1), most initial deforestation is linked to pasture.

3.2 Dataset construction

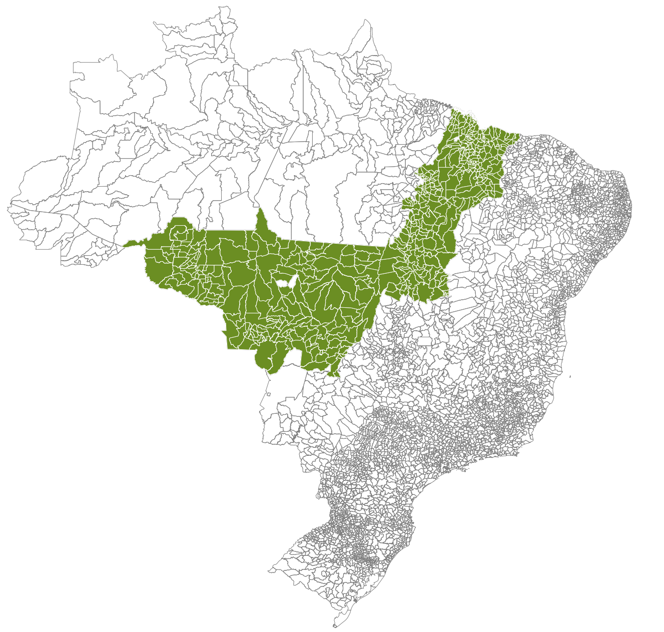
My sample consists of 533 municipalities that have seen high rates of deforestation. These lie along the Southwest frontier of the Amazon, which has come to be known as the 'arc of deforestation'. Figure 1 shows the locations of these municipalities in Brazil. For each of these municipalities, I collect data on the annual deforestation rate and returns to beef and soy production (or beef and soy *prices*, respectively) .

Deforestation rates are measured using remotely sensed data. I use the landcover maps from the MapBiomas project (Souza et al. 2020)[9]. These maps are constructed using 30m×30m pixels from LANDSAT satellite imagery. Each pixel, which in its raw form is a composite of different wavelengths, is classified into different land cover types using supervised learning algorithms trained

[8]Besides indigenous peoples and the few government-led settlement programs, most of the land in the Amazon has been autonomously settled by ranchers and farmers since the 1960s. Private properties often have large sections of standing forests. The Brazilian forest code currently requires 80% of private properties in the Amazon to remain under forests, though there is difficult to implement and often not adhered to. Much of the land in the Amazon is still in public domain, protected as reserves as well as unprotected. Deforestation is prevelant in all of these domains, though there is some evidence that assigning land tenure as well has protected areas have led to reduction in deforestation rates (Tseng et al. 2020; Lipscomb and Prabakaran 2020; Andam et al. 2008; Probst et al. 2020).

[9]MapBiomas Project is a multi-institutional initiative to generate annual land cover and use maps using automatic classification processes applied to satellite images. The complete description of the project can be found at http://mapbiomas.org. I use version 4.1, which was the latest available data when the computations for this paper were done.

Figure 1 Location of sample municipalities in Brazil



using groundtruth data. The final classification puts each pixel in one of 27 different land cover types. For my purposes, I consider two coarser categories: 'natural forest'[10] (or, just *forest*) and 'pasture'. Starting in the year 2000, I label the first year when a pixel transitions from forest to pasture as the deforestation year for that pixel. Then, for each year-municipality pair, I aggregate the pixels that were deforested to calculate total deforestation for each municipality for each year. Given this measure of deforestation, I define deforestation rate for municipality i in year t as

$$d_{it} = \frac{\text{deforestation}_{it}}{\text{area under forest for } i \text{ in year 2000}} \tag{1}$$

The local price variable is constructed using two sets of data - an aggregate (national level) price series and a local transportation cost. CEPEA, an economic research agency associated with the University of Sao Paulo, constructs a daily cattle price index based on prices of closed trades in the spot markets in the state of Sao Paulo. I construct an annual price series by averaging this index for the months of July-September[11], the dry season, when most deforestation occurs in the

[10]Natural forests include natural savanna, mangroves as well as natural rainforest land cover types - and exclude plantations.

[11]I also estimated the model using the average for the entire year, as well as the maximum price during the year,

Amazon. The transportation cost is based on a optimization routine that calculates the lowest cost of transporting a unit of beef from each municipality to each of the ten ports in the region that export beef. This optimization uses the Brazilian transportation network, including waterways and accounting for quality of infrastructure, and annual variation in fuel prices. The transportation cost is measured as the cost to the best (in terms of transportation cost) port. Note that, among other things, switching between modes of transport implies that the for any municipality the best port might change year to year. The local price is defined as the difference between the Sao Paulo price series and municipal transportation cost.

For some of the analysis, I also use a local soy price that has been similarly constructed.

3.3 Descriptive statistics

Table 1 provides summary statistics for the two variables as defined above. It must be noted that the seemingly low deforestation rates correspond to large tracts of deforested land, as each municipality is geographically large - the median municipality has an area of 15,000 ha.

Table 1 Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
beef price ($/kg)	5,841	2.525	1.853	0.248	6.896
deforestation rate (%)	5,841	0.869	0.985	0.001	11.819

Figure 2 shows the geographical distribution of deforestation and beef prices in Brazil. It plots the time average of deforestation rates and beef prices for the sample of municipalities considered in the paper.

Figure 3 presents a depiction of time series variation in the data. The solid lines plot the cross-sectional averages of the two variables over time. The scatter points around each line show the cross-sectional distribution of each of the two variables for each year. Figure 3 shows the sharp drop in deforestation in 2004 and 2008. It also shows that most of the variation in prices is the time series variation, whereas there is relatively more dispersion in the cross-section of deforestation rates.

but results do not change substantially.

Figure 2 Geographical distribution of deforestation rates and beef prices

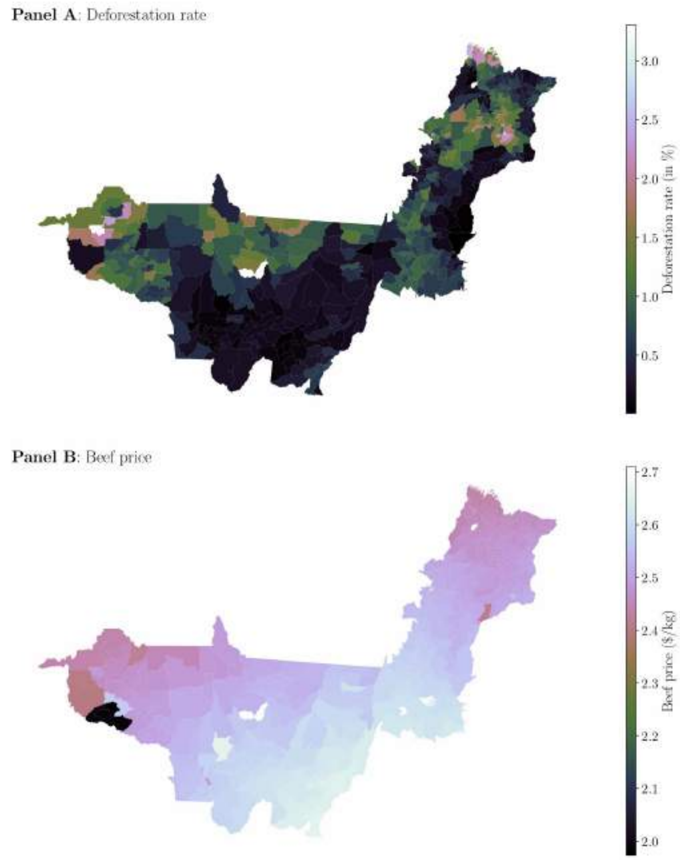
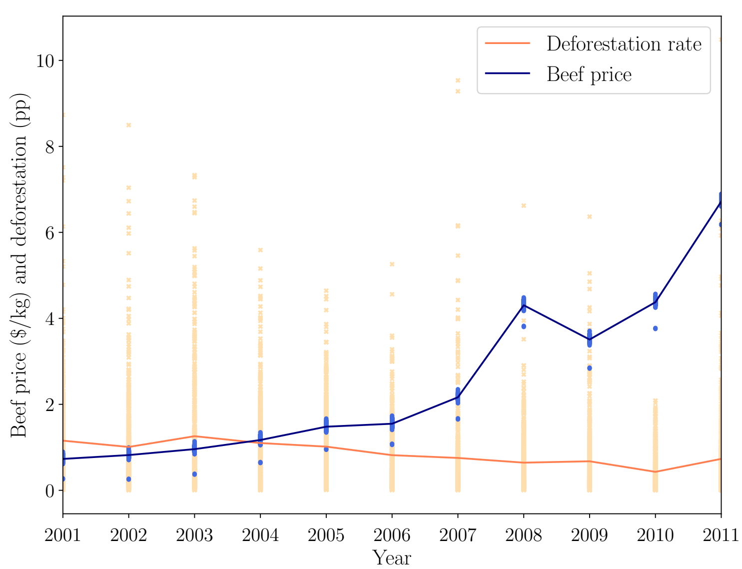


Figure 3 Time series and cross-sectional variation in data



The regressions in Table 2 and Table 3 document two key empirical facts that drive the structural analysis of this paper. I do not claim these as causal relations, rather controlled correlations that merit further investigation. This paper investigates one possible mechanism that could generate these correlations.

Table 2 Reduced form correlations: Variables in levels

Dependent variable: d_{it}

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FD	FD	FD
p_t	0.083	-4.363***	-5.084***	0.559	-1.804**	-2.200**
	(0.437)	(0.450)	(0.896)	(0.692)	(0.686)	(0.697)
p_{t-1}		-1.336***	-0.960*		-0.346	-0.246
		(0.202)	(0.457)		(0.350)	(0.274)
p_{t-2}		-1.587***	-0.565		-1.436***	-1.026***
		(0.057)	(0.454)		(0.138)	(0.135)
p_{t-3}		6.123***	4.985***		2.957**	2.615***
		(0.542)	(1.380)		(0.837)	(0.536)
N	5,841	4,248	4,248	5,310	3,717	3,717
Controls	Policy	Policy	Policy + soyprice	Policy	Policy	Policy + soyprice

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is deforestation rate, as defined (1). Columns (1)-(3) include municipality fixed-effects and estimate the model using a within-estimator. Columns (4)-(6) eliminate these fixed using first differences. All columns also include dummies for post-2004 and post-2008 to control for national level policies; columns (3) and (6) also control for local soy prices. Standard errors are clustered by year.

The first empirical fact is that there is a negative or (statistically indistinguishable from) zero association between contemporaneous prices and deforestation rates. This is true when both variables are measured in levels (Table 2) as well as in logs (Table 3). This holds even after controlling for municipality fixed-effects, national level policies and local returns to soy, and regardless of the estimation method (fixed-effects or first differences). The negative association becomes apparent after controlling for lags of prices.

The second empirical fact concerns the lag structure of this correlation and also holds for all the above specifications. As seen in columns (2)-(3) and (5)-(6), there is a negative association between 0-2 lags of prices and current deforestation, but this correlation is positive at the third lag. This is consistent with the effect of a price shock persisting for three years. Interestingly, the lifecycle of beef cattle in the Amazon is also typically of the same duration.

Similar patterns have also been noted by other studies, including Assunção, Gandour, Rocha, et al. (2015), which similarly hypothesizes the role of cattle dynamics in driving these patterns. However, they do not explore it in more detail.

Table 3 Reduced form correlations: Variables in logs

Dependent variable: $\ln d_{it}$

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FD	FD	FD
p_t	-0.380	-0.590***	-0.541***	-0.047	-0.254	-0.211
	(0.234)	(0.128)	(0.118)	(0.417)	(0.219)	(0.157)
p_{t-1}		-0.022	-0.089		0.056	0.059
		(0.049)	(0.072)		(0.096)	(0.077)
p_{t-2}		-0.718***	-0.769***		-0.706***	-0.713***
		(0.028)	(0.047)		(0.053)	(0.043)
p_{t-3}		0.660***	0.746***		0.393*	0.388**
		(0.085)	(0.069)		(0.164)	(0.122)
N	5,841	4,248	4,216	5,310	3,717	3,665
Controls	Policy	Policy	Policy + soyprice	Policy	Policy	Policy + soyprice

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the log of deforestation rate, as defined (1). Columns (1)-(3) include municipality fixed-effects and estimate the model using a within-estimator. Columns (4)-(6) eliminate these fixed using first differences. All columns also include dummies for post-2004 and post-2008 to control for national level policies; columns (3) and (6) also control for local soy prices. Standard errors are clustered by year.

4 Model

I model a representative[12] rancher who chooses how much of adult cattle stocks to slaughter, as well as how much additional pasture to create for the herd to grow. Slaughter cattle c_t is sold at price p_t. This price is realized during period t, after which the slaughtering decision is made.

Now I describe cattle biology. Slaughtering happens from adult stocks. Let b_t be the adult *breeding* stock at the beginning of period t. Each breeding individual gives birth to k offsprings at the beginning of period t, after which δ fraction of the adults die. These kb_t offsprings will now grow for $m-1$ years and will join the adult stock at the end of period $t+m-1$, which means they will become a part of the breeding stock for period $t+m$ and are available for sale at price p_{t+m}. Following this logic, at the beginning of period t, $(1-\delta)b_t$ cows are available for slaughter. This gives the law of motion for cattle stocks

$$b_{t+1} = (1-\delta)b_t - c_t + kb_{t-m} \tag{2}$$

Using this, we can write the problem in terms of b_{t+1}, rather than c_t. The rancher cannot slaughter more stock than available to him, and cannot slaughter negative stocks. These constraints

[12]When estimating the model, I will take a municipality to be a representative rancher, with each municipality acting independently of others.

on c_t imply that

$$b_{t+1} \geq kb_{t-m}$$
$$b_{t+1} \leq (1-\delta)b_t \tag{3}$$

In addition to cattle stocks, the key input in beef production is pasture. Pasture imposes a soft capacity constraint on how much cattle can be feasibly sustained. I model overcrowding or congestion as affecting the contemporaneous revenue e.g. through higher management/labor costs, buying feed from the market. As will be apparent below, this modeling assumption has the benefit of simplifying computations as well as helping with identification.

Storing Cattle. Suppose a rancher has access to a large forest and has already deforested (and therefore converted to pasture) l_t units. Let $\mathbf{b}_t := (b_{t-m}, b_{t-m+1}, \ldots, b_t)$. Note that along with the law of motion (2), $\mathbf{b}_t$ is sufficient to determine the age profile of cattle stocks. The assumption is that all of breeding stock, even if from different cohorts, is homogeneous. I model the capacity constraint as a *congestion* or overcrowding cost $q(\mathbf{b}_t, l_t, \xi_t)$ which enters contemporaneous returns. Congestion can arise from cattle of all age groups because all animals need to be fed. However, older animals have a higher nutritional requirement than younger ones, therefore impose a bigger burden on existing capacity. I assume that this per capita nutritional requirement, α_j, depends only on the age j of the animal (and does not depend on the size of the herd).

This setup allows me to define the pasture requirement, $l_t^R(\mathbf{b}_t)$, corresponding to any given age profile, $\mathbf{b}_t$. To see this, consider how age profile maps to $\mathbf{b}_t$. Let s_{at} denote the size of the stock of age a at time t.

$$\begin{aligned} s_{0t} &= kb_t \\ s_{1t} &= kb_{t-1} \\ &\vdots \\ s_{(m-1)t} &= kb_{t-(m-1)} \\ s_{mt} &= b_t(1-\delta) + kb_{t-m} \end{aligned}$$

where m refers to ages m and above. The input requirement is

$$\alpha_0 s_{0t} + \alpha_1 s_{1t} + \ldots + \alpha_m s_{mt} = \Sigma_{\tau=0}^{m} k\alpha_\tau b_{t-\tau} + \alpha_m b_t(1-\delta) =: l_t^R$$

This implies that $\mathbf{b}_t$ only enters the $q(.)$ function as a linear index:

Assumption 1. a.:

$$q(\mathbf{b}_t, l_t) = q(\Sigma_{j=0}^{m} \alpha_j b_{t-j}, l_t)$$

The interpretation is also straightforward. The idea is that there is a fixed input, typically forage or feed, requirement for each animal of a given age. This notion is commonplace in the cattle rearing industry, where the concept of Animal Unit (AU) equivalences is used to determine feed requirements. More generally, inputs could also include managerial effort - the substantive assumption in this case is that these too are required in fixed proportions for each animal class. The function captures the idea that if there are "excess stocks" $\Sigma_{j=t-m}^{t} \alpha_j b_j$ relative to "capacity" l_t, then the rancher pays a revenue cost.

The linear index assumption also makes identification possible. As will be evident below, it implies that only observed contemporaneous variables (and parameters) appear in the intratemporal first order condition. The other assumption that enables this is quasilinearity of $q(.)$ in the first argument.

Assumption 1. b.:

$$\frac{q_1'(\mathbf{b}_t, l_t)}{q_2'(\mathbf{b}_t, l_t)} = -1.$$

I assume that the ratio is a constant, which is normalized to -1.

An example of the congestion function that satisfies both of the above assumptions is

$$q(\Sigma_{j=0}^{m} \alpha_j b_{t-j}, l_t, \xi_t) = \max\left\{0, \left(\Sigma_{j=0}^{m} \alpha_j b_{t-j} - l_t\right)^{\rho}\right\}, \quad \rho > 1$$

Deforestation. In addition to holding cattle stocks, the rancher has to decide on capacity expansion. At the end of period t, he chooses how much more to deforest, d_t. Forest clearing is *irreversible*; one unit of land cleared for be pasture forever. Therefore, the deforestation choice d_t amounts to choosing l_{t+1}.

The deforestation cost for the representative rancher is given by $C(d_t, \eta_t)$, where η_t is a cost shifter. This cost is the analogue of conversion costs (or switching costs) in the land use literature. I assume this to be convex, which allows for local scarcity of deforestation inputs.[13]Relatedly, it also

[13]We can microfound this using a simple supply demand model. Suppose each municipality is populated by a unit measure of identical, atomistic ranchers, indexed by i. Suppose a composite input I is required for deforestation, with the production function given by $d_{it} = f(I_{it})$, where $f' \geq 0$. The derived demand for I_{it} must satisfy $I_{it}^{D} = f^{-1}(d_{it})$, where d_{it} is the deforestation choice. The input I is supplied in a local (municipal) market. Assuming that this input cannot be stored, there are no fixed costs of producing the input and that the functional form of the composite does

includes punishments or fines that might be levied due to illegal deforestation (Börner, Marinho, and Wunder 2015).

Assumption 2. a.: $C(d_t, \eta_t)$ is differentiable and the marginal cost is increasing in deforestation $C_1'(d_t, \eta_t) > 0$.

Assumption 2. b.: No reforestation:

$$d_t \geq 0 \tag{4}$$

Prices. Finally, I assume that the rancher is a price taker and the price process is first order Markov, exogenously given. This is consistent with the assumption of an atomistic rancher

Rancher's problem. Now, I can define the rancher's optimization problem

$$\begin{aligned} V(\mathbf{b}_t, l_t, p_t) = \max_{b_{t+1}, l_{t+1}} & \; p_t c_t - q(l_t^R, l_t, \xi_t) - C(d_t, l_t, \eta_t) \\ & + \beta E_t V(\mathbf{b}_{t+1}, l_{t+1}, p_{t+1}) \end{aligned}$$

subject to (3) and (4).

At an interior solution, we have the following first order condition for b_{t+1} in period t

$$\begin{aligned} 0 = & \underbrace{-p_t}_{\text{foregne revenue from saving marginal cow}} \\ & + \underbrace{\beta(1-\delta)E_t p_{t+1} - \beta(1-\delta)\alpha_m q_1'\left(\mathbf{b}_{t+1}, l_{t+1}\right)}_{\text{revenue next period selling marginal cow, net of marginal cogestion}} \\ & + \underbrace{\beta^m k E_t p_{t+m} - \Sigma_{\tau=0}^m \beta^{\tau+1} k \alpha_\tau E_t q_1'\left(\mathbf{b}_{t+\tau+1}, l_{t+\tau+1}\right)}_{\text{revenue from selling progeny of marginal cow } m \text{ periods later, net of cumulative marginal congestion}} \end{aligned} \tag{5}$$

---

not vary, the market supply curve is given by

$$S(p_{it}^I) = I_{it}^S, \qquad S' > 0$$

where p_{it}^I is the market price of the input. The upward sloping supply curve captures increasing marginal cost of supplying the input. Equilibrium in the local market implies

$$S(p_{it}^I) = f^{-1}(d_{it}) \implies p_{it}^I = S^{-1}\left(f^{-1}(d_{it})\right)$$

This equilibrium price p_{it}^I captures the marginal cost of deforestation for the representative rancher. In other words,

$$C'(d_t) = S^{-1}\left(f^{-1}(d_{it})\right).$$

Note that $C' > 0$ as long as $S' > 0$, even if $f' = 0$.

and for d_t in period t

$$\underbrace{C_1'(d_t,\eta_t)}_{\text{marginal cost of } d_t} = - \underbrace{\beta q_2'\left(\mathbf{b}_{t+1}, l_{t+1}\right)}_{\text{marginal congestion benefit of } d_t} + \underbrace{\beta E_t\left[C_1'(d_{t+1},\eta_{t+1})\right]}_{\text{expected marginal cost reduction for } d_{t+1}} \tag{6}$$

The first order condition for b_t is essentially a consumption-saving Euler equation. A marginal cow saved today, time t, leads to a revenue loss of p_t to the rancher. The rancher must also bear the cost of holding this cow (if it survives tomorrow) as well as its k progeny until they grow to be of slaughtering age. This cost is not entirely known today as future congestion depends on future slaughter and deforestation decisions, which, in turn, depend on future price realizations. On the other hand, the marginal cow saved adds to the future revenue stream as it can be sold at p_{t+1} tomorrow, and its progeny sold at p_{t+m}, m periods from now. Similar to costs of saving a marginal cow, these future benefits are uncertain as well. The first order condition dictates that a necessary condition for an interior optimum is that expected costs of the marginal cow saved must equal its expected benefits.

It should be noted that this first order condition implies that following an unanticipated increase in price today, holding fixed future prices as well as future decisions, the rancher optimally chooses to reduce herd size next period. To see this, note that $q_1'' \geq 0$, so the expectation of q_1'' for any future time period must also be weakly positive. This effect was first noted by Jarvis (1974). Of course, in general, we would never observe such a comparative static because prices are serially correlated and future slaughter decisions depend on current slaughter decisions.

The first order condition of d_t similarly reflects intertemporal arbitrage concerns. Clearing an additional unit of land today, which requires the rancher to pay the marginal cost of deforestation today, provides two benefits in the future. First, there is a (weakly positive) reduction in congestion tomorrow. This is the direct benefit from today's deforestation, which is deterministically known today, given the choice of b_{t+1}. However, as deforestation is irreversible and pasture is never destroyed, an additional unit of pasture created today also reduces congestion beyond tomorrow. Interestingly, the Markov nature of the problem implies that the optimal deforestation decision tomorrow is sufficient static for these benefits. The first order condition at $t+1$ implies that these benefits must be equal to the optimal level of marginal cost tomorrow. This leads to the second term in equation 6.

The irreversibility of deforestation creates an incentive to create excess pasture today as an insurance against the scenario where tomorrow's prices might be lower and more capacity might be required. This option value of having excess pasture is tempered by the convex costs of deforestation, which imply an opposing cost-smoothing incentive. This latter incentive has an analog in the exhaustible resource depletion literature following **Hotelling**. In those problems, the decision maker is typically a consumer who gains instantaneous short-lived benefits from the consumption of the exhaustible resource. Under the assumption that

This first order condition does not explicitly feature p_t, which reflects the idea that the effect of price changes on deforestation are mediate by the choice of herd size: $b_{t+j}, \quad j > 1$. Moreover, it is evident from the equation that a decrease in b_{t+1} should optimally be accompanied by an (weak) decrease in d_t.

Putting this together with the discussion above, the model implies that an unanticipated increase in price today, holding future prices and decisions fixed, should reduce b_{t+1} as well as d_t. More generally, as will be clear in the simulations later, with positively autocorrelated prices, the optimal deforestation policy is downward sloping, even after accounting for the fact that a shock today will change the future path of shocks as well as future decisions, which will be taken into account when making today's decision. This implication of the model can explain the negative correlation observed in Table 2 and Table 3. Moreover, it highlights the potential for a downward bias in any approach that does not take into account the dependence of deforestation on cattle dynamics.

Equation (8) has two implications. First, it provides conditional moment equalities for estimation using Euler-equation GMM approach. Second, (8) can be used to solve for the optimal policy $d_t(p_t)$ without requiring any information on b_t, as long as we know α_js. This is possible because of the fixed-proportions land requirement assumption.

5 Estimation

In this section, I first discuss how the first order conditions derived above can be combined to eliminate the cattle stock state variables and develop a rational expectations Euler equation GMM approach that does not require data on b_t. This will allow me to estimate the deforestation cost parameters. Next, I discuss the calibration of agronomic parameters of my model and specify the functional forms I use in this estimation. Finally, I discuss how I measure short-run and long-run responses of deforestation.

5.1 Deriving the estimating equation

The key to eliminating the the endogenous unobserved states, or b_{t+k} terms, is the realization that optimality requires not only lack of intertemporal arbitrage opportunities but also *intratemporal* arbitrage opportunities. Intuitively, the approach can be summarized by the following equalities

$$\begin{aligned}\text{MC deforestation} &= \text{MB deforestation}\\ &= \frac{\text{marginal congestion from saved cattle}}{\text{land use intensity } (\alpha)} = \text{net MR from cattle saved}\end{aligned}$$

Here, the first equality is the intertemporal optimality condition for deforestation and the third equality is the Euler equation for cattle. The second equality follows from the fact that for every t, at the optimum, the marginal benefit from deforestation, which comes from reduced congestion, must be consistent with the congestion levels implied by the choice of b_{t+1}.

Formally, I can use the first order condition for d_t to iteratively substitute out the b_{t+k} terms from the first order condition for b_{t+1}. To see this, rearranging (6) gives

$$\frac{C_1'(d_t, \eta_t) - \beta E_t\left[C_1'(d_{t+1}, \eta_{t+1})\right]}{-q_2'\left(\mathbf{b}_{t+1}, l_{t+1}\right)} = \beta$$

which implies that

$$\begin{aligned}\beta q_1'\left(\mathbf{b}_{t+1}, l_{t+1}\right) &= \frac{C_1'(d_t, \eta_t) - \beta E_t\left[C_1'(d_{t+1}, \eta_{t+1})\right]}{-q_2'\left(\mathbf{b}_{t+1}, l_{t+1}\right)} \times q_1'\left(\mathbf{b}_{t+1}, l_{t+1}\right)\\ &= -\frac{q_1'\left(\mathbf{b}_{t+1}, l_{t+1}\right)}{q_2'\left(\mathbf{b}_{t+1}, l_{t+1}\right)}\left(C_1'(d_t, \eta_t) - \beta E_t\left[C_1'(d_{t+1}, \eta_{t+1})\right]\right)\\ &= \left(C_1'(d_t, \eta_t) - \beta E_t\left[C_1'(d_{t+1}, \eta_{t+1})\right]\right) \qquad (7)\end{aligned}$$

where the last equality uses Assumption 1.b.

This holds for every period, therefore I can substitute out the marginal congestion terms for each period from (5) using (7).

$$0 = E_t\left\{-p_t + \beta(1-\delta)p_{t+1} + \beta^m k p_{t+m} + \Sigma_{\tau=0}^{m+1}\left[\gamma_\tau C_1'(d_{t+\tau}, \eta_{t+\tau})\right]\right\} \qquad (8)$$

where $\gamma_{j\tau}$s are constants (functions of model parameters, including α_js)

$$\begin{aligned}\gamma_0 &= -\left[(1-\delta)\alpha_m + k\alpha_0\right] < 0 \\ \gamma_1 &= \beta(1-\delta)\alpha_m + \beta k\left(\alpha_0 - \alpha_1\right) \\ \gamma_j &= \beta^j k\left(\alpha_{j-1} - \alpha_j\right) \text{ for } m \geq j \geq 2 \\ \gamma_{m+1} &= \beta^{m+1} k\alpha_m,\end{aligned}$$

where the first line corresponds to the FOC for d_t and the second to FOC for b_{t+1}.

At this point, I introduce the rational expectations assumption. The assumption states that the expectation formation process used in the model, which in my case is the mathematical expectation over the stochastic price process, is the same as that employed by the agents in the data. In other words, the theoretical model is consistent with the data generating process. Under this assumption, (8) implies

$$E\left[-p_{it} + \beta(1-\delta)p_{it+1} + \beta^m k p_{i,t+m} + \Sigma_{\tau=0}^{m+1}\left[\gamma_\tau C_1'(d_{i,t+\tau}, \eta_{i,t+\tau})\right] \middle| Z_{it}\right] = 0$$

where $p_{i,t+j}$ and $d_{i,t+j}$ are realizations of prices and deforestation, respectively, and Z_{it} is any variable in the information set at time t, for municipality i. Therefore, the rational expectations assumption allows me to relate the theoretical model to the data.

This conditional moment equality can be converted to an unconditional moment equality

$$E\left[\left(-p_{it} + \beta(1-\delta)p_{it+1} + \beta^m k p_{i,t+m} + \Sigma_{\tau=0}^{m+1}\left[\gamma_\tau C_1'(d_{i,t+\tau}, \eta_{i,t+\tau})\right]\right) \cdot Z_t\right] = 0 \tag{9}$$

The γ_j parameters, are functions of agronomic constants, which I calibrate using existing literature, and the discount rate β, which is set to 0.9. With this and a suitable choice of Z_t variables, I can (nonparametrically) identify the marginal cost of deforestation, C_1', as well as estimate it, using a GMM framework.

This approach is similar to estimating consumption-based CAPM models (Hansen and Singleton 1982). Following that literature, I use $1, d_{t-1}, d_{t-2}, l_{t-1}$ and p_{t-1} as my "basic instruments". If these variables are valid instruments, then so is any function of these variables. Therefore, I use tensor products of the basic instruments in the GMM estimation. In other words, I take products of ordinary polynomials of these basic instruments such that the higher total power is less than equal to a number v. I estimate the model for different values of v. I do two-step GMM, where the first stage estimates are used to construct the weighting matrix for the second stage. In the second stage, the variance-covariance matrix of moments is clustered by year, using the methodology described in Hwang (2020).

5.2 Parametrization and Calibration

For parametric estimation, I need to specify a functional form for $C(d_{i,t+\tau}, \eta_{i,t+\tau})$. I parametrize the cost function

$$C(d_{it}) = \exp(\eta_t) d_{it}^{\theta_1}, \theta_1 > 1.$$

In this specification, $\exp(\eta_t)$ is a time "fixed-effect". I include this to take into account nation-wide deforestation policy changes in Brazil. Accordingly, I estimate three different values of η_t: pre-2004, 2004-08, and post-2008. θ is the convexity of the deforestation cost and captures local scarcity of inputs as explained above.

For each municipality, d_{it} and l_{it} are scaled to be between 0 and 1. d_{it} is "level" of deforestation - area deforested as a fraction of total forest area in 2000. This definition is consistent with the model.

I calibrate the values of the cattle biology parameters k and δ, as well as the factor intensity parameters $\alpha_j s$, from the agronomy literature (though these could be estimated as well). The average cattle growth period for this region of Brazil is 3 years, so I set $m = 3$. The calibrated parameters are given in Table 4.

Table 4 Calibrated agronomic parameters

Parameter	Value
δ	0.24
k	0.05
α_0	0.42
α_1	0.62
α_2	0.62
α_3	1.00

5.3 Limitations of reduced form analysis and need for a structural model

Before proceeding to discuss the estimation of the model, I clarify when we can expect the deforestation policy function to be downward sloping in prices. The discussion also provides intuition behind the underlying theory. To simplify exposition, for this section assume that

$$C(d_{it}) = \frac{\eta}{2} d_{it}^2.$$

Also, in line with the calibration, set $m = 3$. Therefore, (8) becomes

$$E_t \left[-p_{it} + \beta(1-\delta)p_{it+1} + \beta^3 k p_{i,t+3} + \Sigma_{\tau=0}^4 \left[\eta\gamma_\tau d_{i,t+\tau} \right] \right] = 0$$

I can rearrange terms and write

$$d_{it} = \frac{1}{\eta\gamma_0} p_{it} - \frac{\beta(1-\delta)}{\eta\gamma_0} E_t p_{it+1} - \frac{\beta^3 k}{\eta\gamma_0} E_t p_{i,t+3} - \Sigma_{\tau=1}^4 \frac{\gamma_\tau}{\gamma_0} E_t d_{i,t+\tau}, \tag{10}$$

where $\gamma_0 < 0$.

This is the "true" structural equation. The "explanatory" variables that determine deforestation include not just contemporaneous price p_{it} but also forecasts of both prices as well as future deforestation rates. Intuitively, price forecasts matter because they determine profitability of saving an additional cow today.

Assuming that prices are first-order Markov, the deforestation policy function will also be first-order Markov. Denote this optimal policy by $d^*(p)$. Suppressing the i subscript, (10) can be written as

$$d^*(p_t) = \frac{1}{\eta\gamma_0} p_t - \frac{\beta(1-\delta)}{\eta\gamma_0} E_t p_{t+1} - \frac{\beta^3 k}{\eta\gamma_0} E_t p_{t+3} - \Sigma_{\tau=1}^4 \eta \frac{\gamma_\tau}{\gamma_0} E_t d^*(p_{t+\tau}). \tag{11}$$

Regressing deforestation rates on (exogenous) variation in prices can at best non-parametrically recover the structure of $d^*(p)$. However, this is of limited use in understanding how deforestation might respond to changes in structural features of the economy such as efficiency of pasture (which governs $\gamma_j s$) or, more relevant to this paper, the stochastic process of prices (which governs as $E_t p_{t+\tau}$). To see this, note that (11) is an implicit equation in $d^*(p)$. Therefore, the solution to $d^*(p)$ depends on the values of equation parameters, such as γ_j and $E_t p_{t+\tau}$. Any change in these parameters will change the optimal $d^*(p)$. However, the realized data correspond only to specific values of the parameters, and therefore, the estimate of $d^*(p)$ based on those data is not consistent with a different set of parameters. This is an example of the Lucas critique (Lucas 1976).

To address this issue, in the context of this simplified example, I estimate the unknown η given the data. Holding η fixed, I change some of the parameters and solve for a new policy function $\tilde{d}(p)$ consistent with the new set of parameters. To understand the effect of a change in this set of parameters, I simulate deforestation rates under $\tilde{d}(p)$ and compare them to data simulated under $d^*(p)$.

I can also use (11) to get partial effect of a time t price change:

$$\frac{\partial d^*(p_t)}{\partial p_t} = \frac{1}{\eta\gamma_0} - \frac{\beta(1-\delta)}{\eta\gamma_0}.\frac{\partial E_t p_{t+1}}{\partial p_t} - \frac{\beta^3 k}{\eta\gamma_0}.\frac{\partial E_t p_{t+1}}{\partial p_t} - \Sigma_{\tau=1}^{4}\frac{\gamma_\tau}{\gamma_0}E_t\frac{\partial d^*(p_{t+\tau})}{\partial p_{t+\tau}}.\frac{\partial E_t p_{t+\tau}}{\partial p_t} \tag{12}$$

(12) highlights the factors affecting the slope of $d^*(p)$. Note that $d^{*\prime}(p)$ appears on both sides of the equation, albeit evaluated at different values of p. The sign of $d^{*\prime}(p)$ depends on several factors. First, we must account for the autocorrelation of prices. Second, we must account for the coefficients on each of the terms in the expression. Note that some of the coefficients on the $\frac{\partial E_t d^*(p_{t+\tau})}{\partial p_t}$ term do not have an unambiguous sign. In particular, $\gamma_1 = \beta(1-\delta)\alpha_m + \beta k(\alpha_0 - \alpha_1)$ is positive only if $(1-\delta)\alpha_m > k(\alpha_1 - \alpha_0)$, which is an empirical question.

5.4 Quantifying the response of deforestation to price changes

I need to estimate a price process in order to perform counterfactuals for different parameters of the price process. Note that the estimation above does not depend on estimates of the price process. This is a relative strength of this approach as it avoids issues arising from a misspecified shock process. Moreover, even though I have used a shorter panel for the above estimation due to limited data at the municipality level, I can now use a longer single time series to estimate this process. To keep things simple, I estimate an AR(1) in logs specification for prices:

$$\ln p_t = \mu + \rho \ln p_{t-1} + \epsilon_t, \qquad \epsilon_t \sim N(0, \sigma_\epsilon^2), \quad p_0 \text{ given} \tag{13}$$

With this process in hand, I consider two types of price shocks. I define a *temporary* price shock as a 10% change in time price, p_0, which is drawn from the stationary distribution of p_t implied by (13). A *permanent* price shock is defined as an increase μ that is equivalent to a 10% change in p_0. In other words, both shocks have the same immediate consequence of increasing p_0 by 10% but have different implications for the realization of stochastic process of price (for a fixed sample path of shocks $\{\epsilon_t\}_{t=0}^T$). A temporary shock changes only the initial condition but not the stochastic process (the markov transition matrix, given the discrete state approximation). A permanent shock changes both.

I consider two types of responses of deforestation to each of these two shocks. First, I measure the *contemporaneous* response - the change in the level of deforestation in the period following the shock. Second, I calculate the change in *long-run* deforestation rate. To define the long-run deforestation rate, I utilize the fact that the model implies that eventually any finite forest will be completely depleted. Normalizing the total size of the forest at time 0 to 1, long-run deforestation rate is given by the inverse of the time to complete depletion. I calculate this rate (or the associated time) both under the baseline as well as the shock scenarios, and compare the difference.

To estimate model implied deforestation statistics for any set of model parameters, I solve the model recursively, over a discrete approximation of the state space. The policy function obtained as a solution to this model is used to simulate the deforestation response to a temporary price change. I simulate multiple price paths, starting at each point on the price grid, and use the model solution to generate the deforestation series associated with these paths. The deforestation statistic (contemporaneous deforestation or long-run rate) is estimated as an average of the same statistic for each of these paths. To measure the uncertainty associated with this estimate, I make multiple draws from the estimated distribution of the model parameters and repeat the above steps for each draw.

6 Results

6.1 Estimates and counterfactuals

Table 5 presents estimates of the cost parameters. Every column of corresponds to a different dictionary of instrument, each corresponding to different v, the highest power of the tensor product. For each of the specifications, the convexity parameter θ, which captures local scarcity of inputs, is estimated to be approximately 3.5. The estimates are sufficiently precise to reject the hypothesis of quadratic costs, corresponding to $\theta = 2$, which implies a linear first-order condition, with a 1% level of significance. Also, the sharp drop in deforestation rates starting 2008 shows up as a high positive value for the $\exp(\eta_{\text{post-2008}})$ parameter. However, beyond these features, these estimates do not have a stand alone interpretation and must be understood based on their implication for the deforestation policy function and counterfactual experiments.

Figure 4 plots the model implied optimal deforestation policy function. Deforestation is expressed in percentage point (pp) terms - it can be thought of as the area deforested from a representative forest of size 100[14]. The estimated parameters imply that this function is decreasing in

[14] I use pp instead of % to avoid the confusion regarding the base used to calculate deforestation rate. Any deforestation rate is calculated over a fixed base of 1 to avoid conflation of actual deforestation with a changing base of total forest remaining in calculating the deforestation rate. My exercise focuses on the former.

Table 5 Estimates of deforestation cost parameters

Max. polynomial power (v)	4	5	6	7
$\hat{\theta}$	3.595	3.482	3.500	3.619
	(0.032)	(0.006)	(0.003)	(0.001)
$\hat{\eta}_{pre-2004}$	1.566	0.777	1.015	1.058
	(51.151)	(48.868)	(57.708)	(0.000)
$\hat{\eta}_{2004-2008}$	0.000	0.060	0.213	0.219
	(0.000)	(0.607)	(6.138)	(0.000)
$\hat{\eta}_{post-2008}$	220,420.535	168,413.685	198,584.869	305,845.952
	(18964.434)	(2559.775)	(1356.465)	(654.570)
Number of instruments	70	126	210	330

Notes: Standard errors are in parentheses.

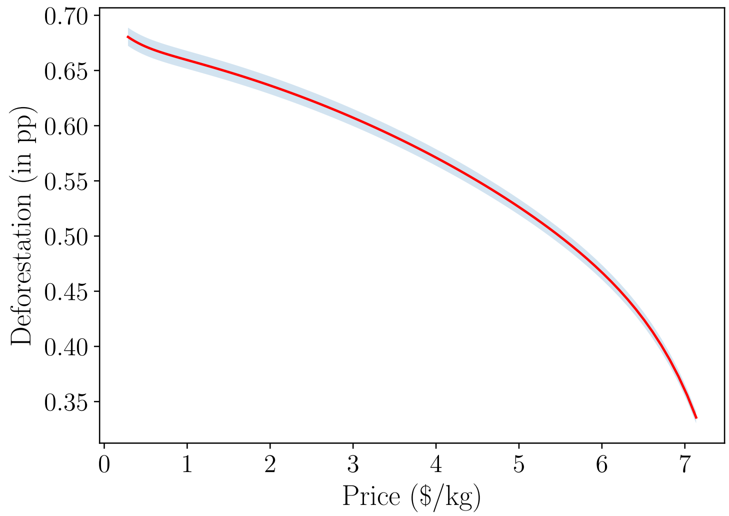
price. The function is quite precisely estimated, despite the apparently large standard errors of the scale parameter of deforestation cost. As discussed before, this function can only tell us about the impact of transitory changes in prices, without any change in fundamentals.

The median model implied deforestation rate is 0.59-0.67 pp (across different specifications), compared to a median value of 0.55 pp in the data. The average model implied deforestation rate is similar, compared to the mean value of 0.89 pp in the data. The model and data cannot be directly compared in this way because the model implied statistics are based on the long-run stationary price distribution, which is not observed in the data. Nonetheless, the similarity between the model and data arises even though the estimation strategy does not explicitly target the deforestation rate, and serves a partial validation of the model.

The estimated time to complete removal of the forest (τ) implied by the model is 163-181 years (across different specifications), which implies an average long-run deforestation rate of 0.55-0.61 pp. The slight difference from the above average deforestation rate arises because τ as an average over multiple sample paths, which do not start out with the long-run stationary markov transition matrix, whereas the average deforestaiton rate in the previous paragraph is calculated using only the stationary distribution of prices. In this sense, deforestation rates based on τ capture dynamics associated with prices, which become important for policy because of the irreversibility of primary deforestation.

Table 6 presents the model based counterfactuals. Panel A corresponds to contemporaneous deforestation and Panel B to the long-run deforestation rate. For all of these counterfactuals, the η_t parameter is set at its post-2008 value.

Figure 4 Estimated deforestation policy function ($v = 5$)



Notes: Deforestation is expressed in percentage points. The shaded grey area represents the 98% confidence interval of the estimated function.

Table 6 Counterfactual estimates of deforestation responses

Max. polynomial power (v)	4	5	6	7
Panel A: Next period level change (in pp)				
Temporary 10% price shock	-0.038	-0.033	-0.031	-0.032
	(0.018)	(0.007)	(0.005)	(0.003)
Permanent 10% price shock	0.026	0.024	0.023	0.023
	(0.011)	(0.005)	(0.003)	(0.002)
Panel B: Time to complete depletion, τ (in years)				
Baseline τ	181.82	172.67	174.48	163.13
	(112.42)	(43.11)	(29.00)	(14.35)
$\triangle\tau$ Temporary 10% price shock	0.75	0.76	0.76	0.74
	(0.05)	(0.03)	(0.02)	(0.01)
$\triangle\tau$ Permanent 10% price shock	-7.60	-7.19	-7.14	-6.39
	(5.30)	(2.02)	(1.35)	(0.62)

A temporary 10% increase in prices leads to a *decrease* in contemporaneous deforestation by approximately 0.031-0.038 pp. This implies a 6% decrease in over the baseline deforestation rate of approximately 0.63 pp. The long-run effects of this increase are determined by the persistence of the price process. Depending on the specification, the long-run effect of this price increase is to reduce τ by 0.7-0.8 years, which implies a 0.44%-0.50% (or a 0.0027-0.0031 pp)[15] change over the baseline deforestation rate of approximately 0.63 pp. This result is *qualitatively* interesting - the

[15] To clarify again, this statistic averages out the impulse response of deforestation over the expected τ, hence the small values.

model, based on *estimated parameters*, predicts that short run increases in beef prices negatively effect deforestation. Quantitatively, as expected, the long-run effect of a one-time temporary price change is likely to be small in the long-run.

A permanent 10% price increase leads to an *increase* in next period deforestation by 0.023-0.026 pp. Note that the permanent change was calibrated to have the same contemporaneous effect on price as a temporary change would. The increase in deforestation is of a similar magnitude as the decrease resulting from a temporary change[16]. The difference in *direction* of response depending on the longevity of price fluctuation, which is a key point of this paper, is evident from this simulation.

As expected, a permanent change in price has persistent long-run effects. However, these effects are quite small. A 10% permanent change in prices reduces τ by 6.4-7.6 years, which implies a 3.7%-4.4% (or a 0.022-0.026 pp) increase over the baseline deforestation rate of approximately 0.58 pp. While the 4% change in deforestation rate might seem big, it a small change in absolute terms. The implication of these results is that long-run deforestation rates are surprising inelastic, even to permanent changes in prices. This is an important finding of this paper.

6.2 Discussion

The above results show that the response of deforestation to short-run and long-run changes in prices can be drastically different - even in terms of direction. The underlying reason for this difference is that both shocks create different incentives for the rancher. From an environmental policy perspective, we are interested in understanding the response to price-based incentives that reduce the demand for deforestation. These include price reduction arising from a secular increase or decrease in global demand for beef, or an improvement in transportation infrastructure that increases returns to beef for areas with increased accessibility. However, as this paper demonstrates, the size of these effects cannot be guaged directly from the data. As a solution to this problem, this paper uses the data to recover some parameters of a theoretical framework, which is then used to make inference about the policy relevant quantity.

A normative implication of dichotomy between short and long-run responses is that policy induced price changes that are expected to be short-lived can create outcomes worse than status-quo. Arguably, policies that are perceived to be a result of fads or temporary appeasement of certain constituents are likely to create such short-lived changes in prices. In the best case, anti-deforestation policies that induce short-lived reductions in beef prices, are unlikely to have large

[16]The slight difference occurs because changing μ also changes the variance of the lognormal price process.

positive effects on deforestation.

Interestingly, under the expectation formation process of the model, it also yields an interesting tool to infer if a given policy is perceived to be short-run or long-run based on the response to that policy. The impact evaluation literature has documented varying degrees of sucess of anti-deforestation policies in the Brazilian Amazon (as well as in other tropical regions). My results indicate that some of these differences might also be due to differences in perceived duration of different policies.

Apart from these qualitative conclusion, the quantitative conclusion from this study is surprising one - deforestation rates are quite inelastic to beef prices. While the prior that temporary fluctuations are less likely to affect deforestation, which is a slow-moving, forward-looking investment, might be reasonable, it is not unreasonable to expect deforestation to be more responsive to permanent changes in (expected) prices. Indeed, land use change in the United States has been shown to be more elastic when accounting for the long-run than short-run covariation in the data would reveal (Scott 2014). However, I find the long-run response to be relatively muted as well.

The implications of the quantitative results of this paper are twofold. First, changes in beef prices in the past have not been the prime movers of deforestation rates. This is apparent from the data presented above and consistent with reduced-form studies such as Assunção, Gandour, Rocha, et al. (2015). Extending this logic further, impacts of any future increases in global demand for beef *that manifests as increases in world prices* is unlikely to spur deforestation rates. In other words, concerns about indirect land use change, as measured by deforestation rates, might be overstated. On the other hand, it limits the scope of anti-deforestation policies or initiatives that work through the price channel. These include civil society initiatives to reduce beef consumption. Note that this is not a result of general equilibrium spillovers or leakage due to relocation of agricultural activity, as discussed in Pfaff and Robalino (2017); instead, it results from parameters implied by the dynamic behavior of a single (representative) agent. As a result, supply side policies that improve efficiency of the cattle sector (Kaimowitz and Angelsen 2008) or increase deforestation costs, such as through improved monitoring (Assunção, Gandour, and Rocha 2013; Börner, Marinho, and Wunder 2015), might be better suited to address excessive deforestation.

On the other hand, note that following a permanent change in prices, the contemporaneous as well as the annualized long-run change in deforestation are *both of a similar magnitude* - approximately 0.02 pp. This implies that permanent policies are likely to have persistent effect, even though small. In principle, it is possible to alter other policy parameters to magnify the price response.

While exploring this complementary is outside of the scope of this paper, permanent price-based policies are likely to provide persistently large gains if other parameters could be calibrated as such.

7 Conclusion

In this paper, I examine how deforestation in the Brazilian Amazon responds to global beef price changes. I model the causal chain from beef prices to deforestation via the cattle management decision of ranchers. I adopt a forward-looking rational expectations framework that highlights the difference between deforestation response to temporary and permanent price fluctuations. Besides a theoretical understanding of the incentives involved, this setup also provides an estimable framework that I use to make quantitatve predictions about short-run and long-run deforestation fluctuations. A purely data based approach cannot recover deforestation responses to permanent price changes because that changes the deforestation policy function, which is what can be recovered from the correlation between deforestation and exogenous variation prices, itself. However, theoretical framework allows me to make long-run predictions without having access to long-run time series. I bring together novel geospatial panel data on local prices and deforestation rates, along with an optimality-based theoretical restriction, to estimate and make quantitative inferences this model.

My approach finds that temporary price increase are *reduces* contemporaneous deforestation rates. This counterintuitive result arises because temporary decreases in prices lead to less slaughter, and therefore a build up of cattle stocks, which requires more pasture, hence more deforestation. While this result is not an unambiguous prediction of the theory, it holds given the estimated model parameters. The second interesting result concerns deforestation responses to permanent price change. A permanent increase in price affects contemporaneous deforestation by a magnitude similar to a temporary increase, albeit in the opposite direction. However, rather unexpectedly, the effect on long-run deforestation rates is small. The twin implications of these results are that long-run indirect land use change might be of limited concern; however, the efficacy of anti-deforestation policies that operate through prices might be limited as well.

These are arguably strong claims - however, they come with several caveats. First, this is a representative agent model, which might hide significant spatial heterogeneity in price responses. Second, there might be interesting general equilibrium or spatial effects that might be working to counterveil some of these effects. For example, there might be complementarities in deforestation decisions, which might create spatial contagions (Robalino and Pfaff 2012) over time - the implication being that small deforestation events might eventually lead to more deforestation in the longer run leading to higher long-run elasticity. Third, the underlying assumption of rational expectations, while a good starting point, might not be ideal in this context. Finally, while this is not a limitation as this paper is intended to be a supply side-analysis, I do not model the demand for beef. The exact level of deforestation will be co-determined with the price level, which depends on both the demand and supply of beef. These are interesting avenues for future research.

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A Additional Figures

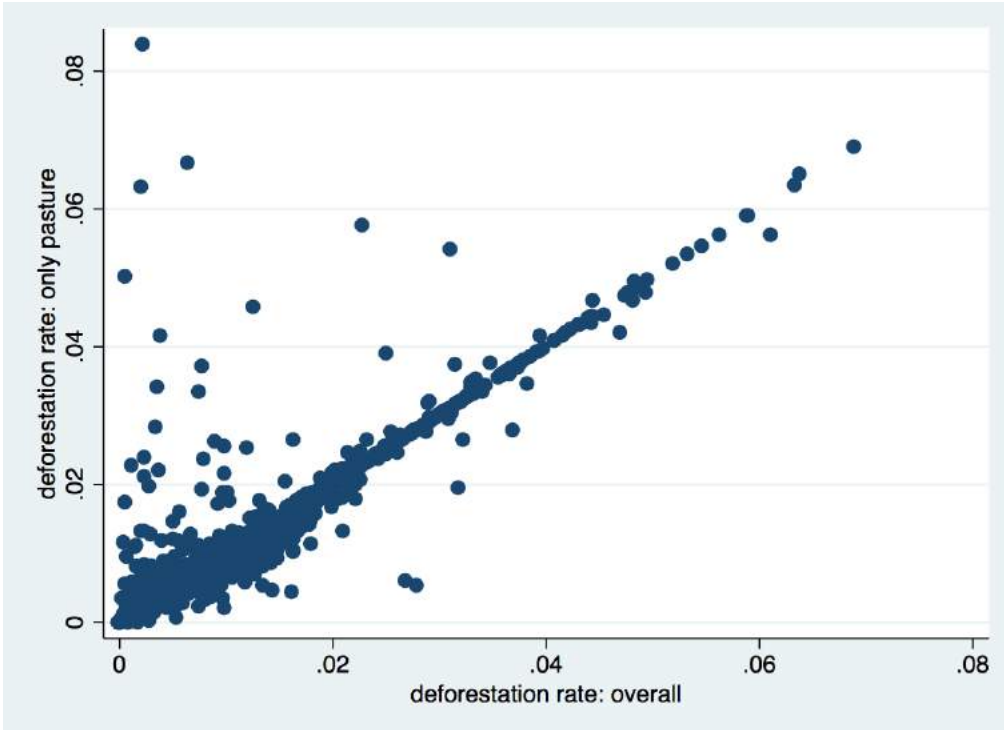

Figure A.1: **Pasture-led vs overall deforestation**

Notes: The figure compares forest to pasture transition rates and forest to all land-cover transition rates. is expressed in percentage points. Each dot represents a municipality-year pair.