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Asset ownership turns climate exposure into inequality

Igor Martins

igor.martins@ekh.lu.se

Lund University https://orcid.org/0000-0002-6141-9273

Stefan Grab

University of the Witwatersrand

Erik Green

Lund University

Article

Keywords:

Posted Date: June 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9859396/v1

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Commodity portfolios mediate climate-driven wealth inequality

Abstract

As climate change alters weather risk, wealth is often treated as a buffer after shocks occur. We show that wealth can shape the economic shock before it arrives by determining which assets households own. In a pre-industrial agrarian society, we link weather to 25,000 household tax records and commodity prices. Households held different production bundles, and the same seasonal weather could raise returns to one bundle while lowering returns to another. Wealthier households more often owned the commodities favoured by observed weather variation, and prices did not systematically offset these differences. These portfolio differences predict next-year changes in movable assets. Years in which weather raised returns to commodities disproportionately owned by wealthier households were years of wider movable-asset inequality. Wealth determined whether weather became loss or gain.

Introduction

Wealth is often treated as protection after climate shocks, allowing richer households to absorb losses and rebuild.[1,2] We ask whether wealth also enters earlier, through the assets by which weather becomes an economic gain or loss.[3,4] We argue that there is no favourable weather profile in general. Rain, wind, heat and cold acquire economic force only when they meet production at a vulnerable point in the season.[5–7] The same weather that weakens one crop can strengthen another, so a year becomes distributional when the rewarded and damaged assets sit in different parts of the wealth distribution.

Climate inequality is therefore an incidence problem. A weather profile reaches inequality by changing output, passing through ownership and prices, and appearing later in reported assets. Wealth can buffer climate impact through portfolio composition before damage appears, as well as through resources available after losses occur. This links evidence on unequal climate damages to a household-level mechanism of ownership and exposure.[8,9]

The pieces of this problem are usually studied apart. Climate-impact research uses year-to-year weather variation to estimate effects on agricultural profits, yields, income and output,[5–7,10–12] and related work follows weather into conflict, migration, political stability and long-run adjustment.[13–17] Yet this literature has more often measured average effects than the distribution of those effects across households, a limitation recent work has made explicit.[18] Inequality history, by contrast, explains wealth distributions through inheritance, markets, institutions, war, demography, land and slavery,[19,20] but has less often treated annual weather as a source of redistribution. Documentary climate reconstruction recovers past weather from non-instrumental sources,[21–27] but its evidence is rarely joined to household-level ownership, production and prices. The empirical difficulty is therefore the absence of a common annual frame linking weather to the social and economic channels through which inequality changed.

Historical evidence is useful because pre-industrial economies leave the climate and wealth relationship closer to the surface, with annual weather reaching production through fewer

technical and institutional buffers while household records allow us to observe the assets through which that exposure was distributed. Such evidence also separates the incidence of weather from the long warming trend that dominates contemporary debate, showing a mechanism that remains relevant as warming changes which weather profiles arrive, and how often, while leaving open whose assets those profiles reward or damage.

The eighteenth-century Cape Colony provides a rare source combination for observing this mechanism at the household level. Three Dutch East India Company (VOC) records can be linked annually, bringing daily weather observations together with the *opgaaf* household tax censuses from the Stellenbosch district and estate-auction price records.[28,29] Stellenbosch was the colony's main agricultural hinterland, where wheat, wine, livestock and enslaved labour were central to production but unequally held across settler households. Because wheat and wine shared winter rainfall while differing in harvest timing, and because livestock followed another exposure path, the same regional climate reached households through different bundles of production and property.

We develop and test an exposure framework for climate inequality in which weather reaches households as commodity-specific value shocks filtered through portfolios and prices. Linking more than 25,000 household-year observations to seasonal weather and price series, we estimate climate responses for wheat, wine and livestock and combine them in a price-weighted Predicted Climate Impact (PCI) index. Weather profiles that damaged wheat often favoured wine, which was concentrated among wealthier households, while wheat and wine prices provide little evidence of systematic offsets against predicted output. The household exposure implied by these commodity responses predicts next-year changes in measured movable assets. Years in which weather raised returns to commodities held higher in the wealth distribution were years of wider measured movable-asset inequality, while annual rainfall carries no comparable signal. The paper shows wealth determining if weather became loss or gain.

Results

Crop calendars gave weather opposing effects

The VOC *dagregisters*, daily administrative diaries kept at the Castle of Good Hope, provide the weather record used here. For 1760–1791 they record rainfall together with wind, heat and cold at the Cape (Fig. 1). The record allows the analysis to follow annual weather as a bundle of seasonal conditions without reducing exposure to rainfall alone. Across the 29 observed climate years, annual rain days range from 53 to 124 and wind days from 32 to 108, while hot and cold days range from none in some years to 35 hot days and 52 cold days in others. Seasonal rainfall also varies strongly, with winter rain ranging from 27 to 72 days and spring rain from 7 to 28 days. The daily categories allow these rainfall patterns to be read alongside harvest wind, summer heat and winter cold. One year could be wet in winter and windy at harvest; another could be near average in rainfall but unusually hot in summer or cold during dormancy. Such combinations are the starting point of the incidence problem, since the same calendar year could enter wheat, wine and livestock at different moments.

The annual weather record intersects the household record through the March *opgaaf* census, whose timing fixes the exposure window for each commodity (Supplementary Table 1). Wheat recorded in March had been harvested from November through February, when wind and heat threatened standing crops and threshing, while wine came from vines harvested mainly in February and March, after the vine cycle had already unfolded. Livestock were counted as stocks at enumeration, so their weather signal combines recent pasture conditions with herd accumulation. The same climate year could produce different commodity shocks before it reached household wealth.

Table 1 reports the commodity regressions described in Methods. Each weather measure is matched to the part of the agricultural year in which that commodity was exposed. The estimates keep the original census units. Wheat is reported in *muids*, a dry measure of capacity equivalent to about 109 litres, and wine in *leaguers*, equivalent to about 516 litres.

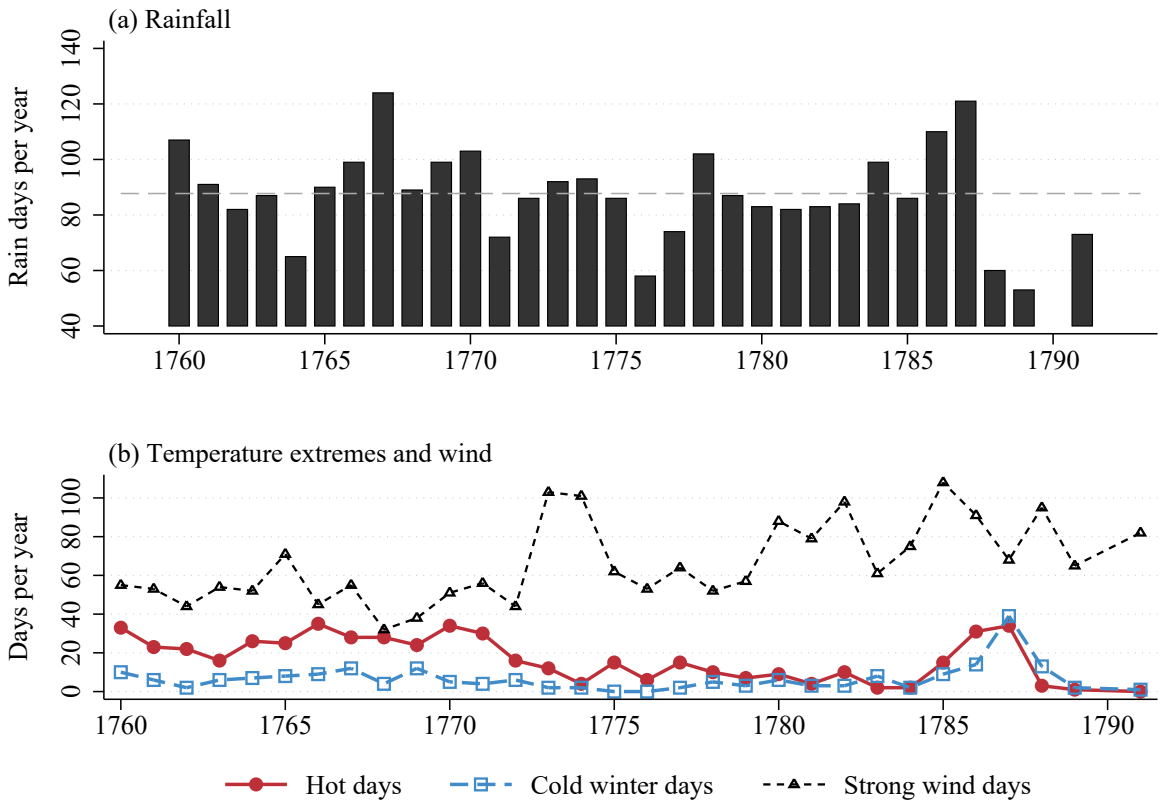


Figure 1: Annual climate conditions at the Cape, 1760–1791. Panel (a) shows rain days by season (bars) and annual total (line). Panel (b) shows wind days, hot summer days and cold winter days. The year 1790 is missing from the primary sources.

For wheat and wine, a coefficient gives the predicted change in those units from one more recorded weather day in that season. For sheep and cattle, it gives the predicted change in head of livestock.

The estimates show why a weather profile has no single economic sign. Rainfall is informative, but its interpretation depends on when it arrived and which commodity was exposed. Growing or winter rain is positive in every commodity column, while spring rain splits the crop and livestock responses. An additional spring rain day is associated with 0.87 more *muids* of wheat and 0.32 fewer *leaguers* of wine. The same rainfall measure is associated with 3.29 fewer sheep and 0.14 fewer cattle. A rainfall-only source would still identify part of the seasonal structure, but it would leave the wind, heat and cold channels unseen.

Table 1: Seasonal climate effects on agricultural output

	Wheat (FD)	Wine (FE)	Sheep (FE)	Cattle (FE)
Rainfall				
Growing / winter rain	0.421***	0.205***	1.941***	0.094***
	(0.137)	(0.022)	(0.256)	(0.025)
Spring rain	0.865***	-0.320***	-3.289***	-0.142***
	(0.278)	(0.047)	(0.485)	(0.050)
Autumn rain	0.372*			
	(0.199)			
Summer rain		0.349***		
		(0.040)		
Wind				
Harvest / vintage wind	-1.153***	0.229***		
	(0.239)	(0.047)		
Total wind			0.757***	0.068***
			(0.130)	(0.013)
Temperature				
Harvest heat / hot days	-0.524***		-4.173***	-0.401***
	(0.169)		(0.442)	(0.036)
Hot ripen		-0.011		
		(0.037)		
Cold winter	1.234***	0.230***	1.371**	0.275***
	(0.276)	(0.052)	(0.576)	(0.044)
R^2	0.076	0.101	0.052	0.035
Observations	1,289	3,589	10,402	13,381
Households	246	506	1,189	1,469

[Notes] Wheat is estimated by first differences (FD) with cross-year agronomic variables; all other commodities by household fixed effects (FE). Wheat and wine use producer-restricted samples. Sheep and cattle use contemporaneous calendar-year climate. Standard errors clustered at the household level in parentheses. Wheat reports R^2; wine, sheep, and cattle report within-R^2. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

For wheat, growing-season rain is positive, as is winter cold. Harvest wind and heat are negative. An additional harvest wind day is associated with 1.15 fewer *muids* of wheat, and an additional harvest heat day with 0.52 fewer *muids*. A ten-day difference in harvest wind, well within the observed range, implies 11.5 fewer *muids* for a wheat-producing household under the fitted relationship. These signs match the crop calendar, with winter moisture and cold supporting establishment and harvest weather damaging standing crops or threshing.

Wine follows a different pattern. Winter and summer rain are positive. Spring rain is negative, while vintage wind is positive. The spring coefficient indicates losses around flowering, while the vintage-wind coefficient indicates gains during harvest. A ten-day difference

in vintage wind is associated with 2.29 additional *leaguers* of wine. The same wind channel that harms wheat at harvest can favour grapes during vintage. Wind becomes favourable or adverse through the crop calendar.

Figure 2 compares wheat and wine directly. Both crops benefited from winter rain, but their responses separated later in the production year, when wind entered the wheat harvest as a damaging condition and the wine vintage as a favourable one. A wet winter followed by a windy harvest could therefore reduce wheat output while increasing wine output, because the same weather profile met the two crops at different moments in their calendars.

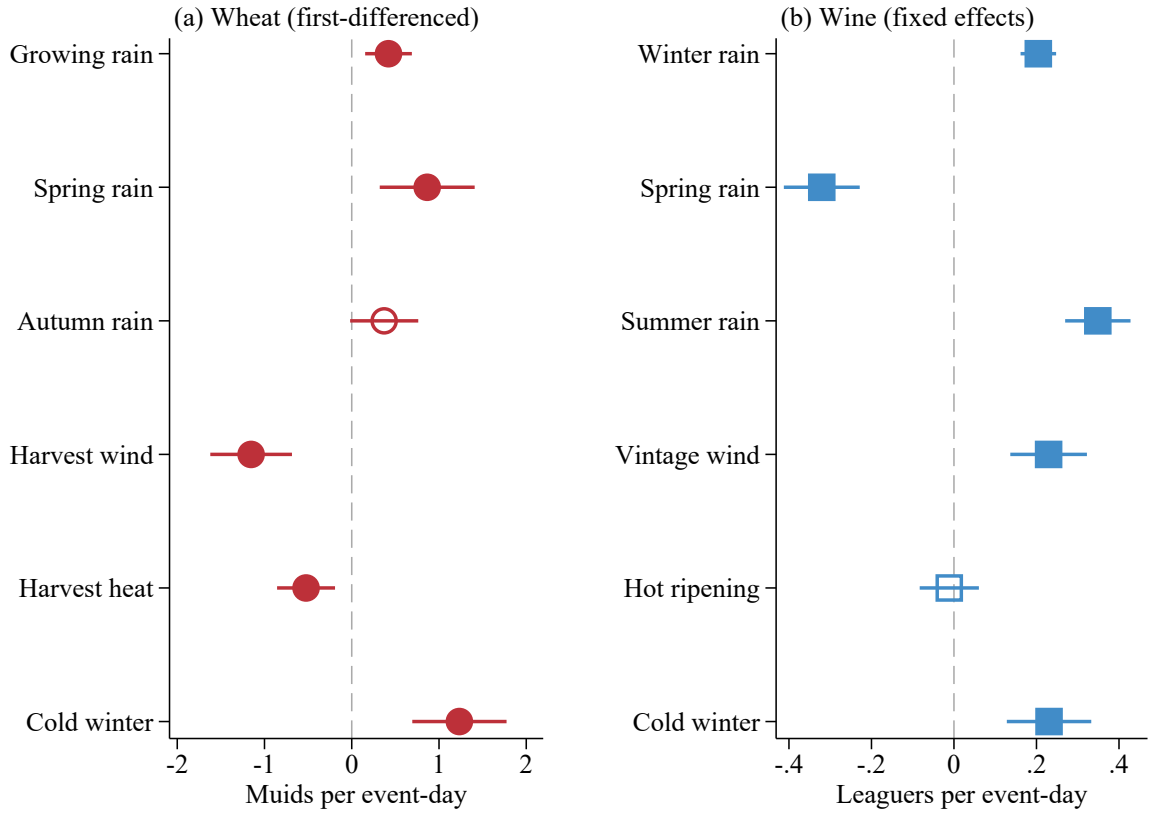


Figure 2: Climate channel coefficients for wheat and wine. Points are estimated coefficients from the multivariate specifications in Table 1; whiskers show 95% confidence intervals. Filled markers indicate significance at 5%. Wheat estimated by first differences, wine by fixed effects, both with cross-year agronomic variables.

Livestock followed another exposure path. Winter rain is positive for sheep, consistent with pasture growth. Spring rain is negative for both sheep and cattle. Heat gives the

strongest livestock signal. One additional hot day is associated with 4.17 fewer sheep and 0.40 fewer cattle. A ten-day hot spell corresponds to 41.7 fewer sheep and 4.0 fewer cattle under the fitted relationship. Cold winter days are positive in the additive specification, though flocks may have remained vulnerable when cold followed wet conditions. The positive wind coefficient for livestock is less secure because wind contains a time-trend confound in these equations. Supplementary Fig. 1 presents standardised coefficients for all commodities.

The crop pattern is also visible among households observed over the long run. Restricting the sample to households present by 1770 and still present after 1780 leaves the main wheat and wine signs in place (Supplementary Table 2). Growing rain remains positive for wheat and harvest wind remains negative; winter rain remains positive for wine and spring rain remains negative. The wheat harvest-wind coefficient is -0.874 in this long-observed sample, compared with -1.153 in the full sample. The wine spring-rain coefficient is -0.301, compared with -0.320 in the full sample. The crop contrast is therefore not produced by short-lived households entering or leaving the panel.

Estimator checks leave the production result unchanged. Wheat is clearest in first differences, where growing rain is positive and harvest wind is negative. Wine keeps the same main signs under first differences and fixed effects (Supplementary Table 3). The alternative wheat specification is used later as a robustness check when the commodity responses are aggregated. At this stage, the result is the opposing crop response itself. Weather reached production through calendars, so the same annual profile could favour one product and damage another.

Ownership sorted climate exposure

The commodity responses estimated above acquire a distributional direction only after they are joined to ownership. The household censuses show where the affected commodities sat in the settler wealth distribution. Bottom-tercile households held an average of 14 *rixdollars* in monetised movable assets and 1.2 enslaved people, while top-tercile households held 2,654

rixdollars and 9.7 enslaved people (Supplementary Table 4). These figures refer to movable productive wealth, capturing the assets most visible in the annual census and the labour force through which production was organised. Because the wealth measure excludes crop output and vines, the production gradients below derive from census production variables, with the asset ranking held separate. Figure 3 shows the same gradient in portfolio composition.



Figure 3: Portfolio composition by wealth tercile. Asset shares of monetised household wealth across enslaved people, cattle, sheep, and horses, by wealth tercile.

Figure 3 shows that the wealth gradient was also a labour gradient. Enslaved people account for 65.1% of monetised movable wealth in the top tercile, compared with 20.1% in the middle tercile and 0.7% in the poorest tercile. Climate exposure among settlers was tied to unequal control over labour as well as unequal ownership of crops and animals, since a household able to maintain vines, livestock and enslaved workers entered the agricultural year with a different exposure profile from a household with little recorded movable wealth.

Crop ownership followed the same hierarchy. Wine appears in 31.8% of household-years in the wealthiest tercile and in 0.2% of the poorest, making it the steepest production gradient in the census. Wheat production also rises with wealth, from 0.1% of poorest-tercile household-years to 19.1% of the wealthiest, but less sharply than wine. Among producers, the same ranking holds, with wheat producers in the top tercile harvesting 77.0 *muids* on average, compared with 46.6 in the middle tercile and 36.0 in the poorest tercile, while wine producers in the top tercile report 22.2 *leaguers* on average, more than twice the middle-tercile mean (Supplementary Table 4).

Livestock occupied a middle position. Sheep holding is rare in the poorest tercile, common in the middle tercile and still more common at the top, while cattle holding reaches 80.7% of wealthiest-tercile household-years. Among sheep holders, mean flock size rises from 163.3 head in the poorest tercile to 392.6 in the wealthiest. Livestock exposure was less concentrated than wine exposure, but it still rose with wealth, so the ownership gradient differed by commodity just as the weather response differed by commodity.

Together, the ownership gradient and the weather coefficients give climate exposure a social direction. Wine was highly concentrated among richer households and responded positively to channels that often reduced wheat, while livestock followed pasture and heat through a separate exposure path. Exposure therefore came from the overlap between commodity response and ownership. The same seasonal profile could widen the distance between households even when aggregate production value rose.

Markets did not erase producer exposure

Prices determine whether a commodity shock remains with producers or is shifted through the market. A poor wheat year, for example, could raise wheat prices enough to offset part of the output loss. If prices do not rise when predicted output falls, producer exposure remains closer to the households that owned the affected commodity. Table 2 tests this price response by regressing the annual price series on predicted commodity output.

Table 2: Commodity prices and climate in year-level regressions

	Wheat price	Wine price	Sheep price
PCI (commodity-specific)	0.086	-0.341	0.002**
	(0.089)	(0.505)	(0.001)
R^2	0.020	0.012	0.121
N	27	27	29

[Notes] OLS with robust standard errors. Each observation is one year. Dependent variable is the annual mean auction price in *rixdollars*. PCI is the commodity-specific Predicted Climate Impact. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The wheat and wine coefficients are statistically indistinct from zero ($p = 0.34, 0.51$). The underlying price series are shown in Supplementary Fig. 2. Sheep prices move in the same direction as predicted sheep output, giving no offset. The price series gives no clear evidence that wheat and wine producers were compensated by systematic inverse price movement, so the portfolio differences above were not undone by annual prices. The pattern fits the Cape's externally connected marketing structure, where local output and prices could move differently across commodities.[28,30,31]

Exposure predicted asset change

The household-level tests examine whether the portfolio exposure measured above appears in later assets. The first step asks whether the same weather variable had different effects across the wealth distribution. Table 3 interacts rainfall with baseline household wealth.

The coefficients show why wealth cannot be treated as uniform protection. Wealthier wheat producers are less sensitive to rainfall variation, while larger sheep holders are more exposed to the same pasture conditions. Doubling household wealth reduces the wheat rainfall response by 0.17 *muids* per rain day and increases the sheep response by 0.27 head per rain day, so wealth buffered one exposure channel and enlarged another.

Figure 4 converts the estimated commodity responses into monetised household impacts. Richer households experience larger absolute swings, largely because of wine exposure, while

Table 3: Climate–wealth interactions

	Rain × ln(wealth)	Doubling effect	N
Wheat	-0.245***	-0.170	2,285
	(0.069)		
Wine	0.041***	0.029	3,723
	(0.013)		
Sheep	0.394***	0.273	10,402
	(0.089)		
Cattle	0.023***	0.016	13,381
	(0.009)		

[Notes] Household fixed effects with standard errors clustered at the household level. Dependent variable is commodity output. Rain is annual rainfall in rain days; for wine, lagged rainfall is used. The interaction uses time-averaged log wealth in *rixdollars*. Doubling effect is $\hat{\beta}_2 \times \ln(2)$. Producer-restricted samples. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

poorer households bear heavier losses relative to measured movable wealth in bad years. The percentage panel clarifies this distributional burden. A small monetary loss can be large relative to the thin asset base of the poorest households, while a larger absolute gain or loss among rich households can remain modest relative to their portfolio.

The figure also separates two kinds of inequality. In *rixdollars*, the upper tercile moves more because it owns the assets through which large monetary gains can occur. As a share of measured wealth, the lower tercile is more exposed because its asset base is thin. That distinction carries into the later split between aggregate inequality and within-poor inequality, where climate exposure can widen the distance between wealth groups while tightening dispersion among households that hold almost none of the favoured commodity.

The second step connects exposure to asset change. The Predicted Climate Impact (PCI) index combines the commodity-specific climate responses with mean prices, so that the realised weather profile is expressed in the monetary value implied by the commodities it affected. Positive PCI years are years in which the estimated commodity responses imply higher net production value for the indexed bundle. They are therefore favourable only to that bundle. Lagged scale-weighted household exposure is positively associated with the PCI ($p = 0.040$), while the crop-only version is not statistically significant ($p = 0.268$; Supplementary Table 5). The spread of household exposure rises in years when realised

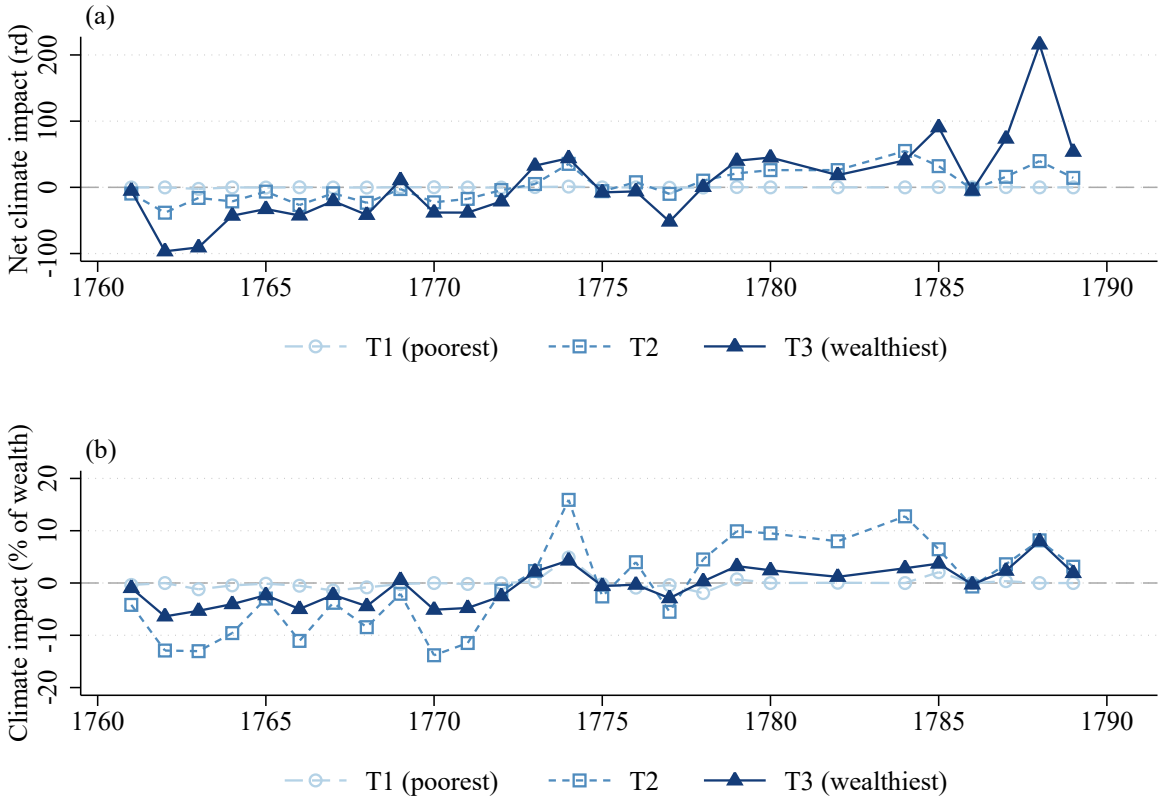


Figure 4: Monetised climate impact by wealth tercile, 1760–1791. Panel (a) shows net climate impact in *rixdollars*. Panel (b) shows net climate impact as a percentage of household wealth.

weather favours commodities that are unevenly owned.

The household accumulation checks carry the exposure calculation into the next year's assets. A one-standard-deviation increase in lagged scale-weighted exposure predicts a 48 *rixdollar* increase in next-year measured movable assets, controlling for current assets and year fixed effects ($p < 0.001$). The crop-only version predicts a 51 *rixdollar* increase in no-livestock assets under the same controls ($p < 0.001$; Supplementary Table 6). Year fixed effects compare households inside the same census year, while current assets control for the starting point from which accumulation occurs. The coefficient asks whether two households observed in the same year, with different exposure to the previous year's realised commodity profile, report different assets in the next census.

The annual exposure diagnostics connect this household result to inequality before the

Gini regressions. The covariance between lagged exposure and lagged wealth is positively associated with current measured-asset inequality ($p = 0.007$). The T3–T1 exposure gap is associated with the current T3–T1 wealth gap ($p < 0.001$), and remains positive with a linear trend ($p = 0.084$; Supplementary Table 6). These tests use the distribution of predicted exposure itself. They show that years favouring commodities held higher in the wealth distribution also have wider measured wealth gaps.

Entry and exit from production are less stable. The wine participation effect disappears under first differences and among stayers. The apparent level response tracks the secular expansion of viticulture (Supplementary Table 7).

Commodity-weighted climate tracked inequality

The annual test asks whether inequality moved with the commodity-weighted climate index. Table 4 estimates annual regressions in which each inequality outcome is regressed on the net PCI expressed as a z-score. Each coefficient gives the change in the inequality outcome associated with a one-standard-deviation increase in predicted net production impact. Across the 27 complete annual observations, the net PCI ranges from 124 to 770 *rixdollars*, with a standard deviation of 122 *rixdollars*. A positive movement in the PCI means that the estimated weather profile raises the value of the commodity bundle in the index. Because that bundle is owned unevenly, the index can increase aggregate production value and widen inequality at the same time, without defining a favourable year for every household.

At the aggregate level, movable-asset inequality rises with the PCI (Panel A, row 1). A one-standard-deviation increase in predicted net production impact is associated with a 0.0088 point increase in the Gini, about half the year-to-year standard deviation of measured inequality in a sample where the annual Gini averages 0.661 and has a standard deviation of 0.017. The regression explains 27.7% of annual variation in the aggregate Gini.

Annual rainfall shows no comparable relationship (row 2). Its coefficient has the opposite sign, is statistically indistinct from zero, and yields an R^2 of 0.015. Annual rainfall cannot

Table 4: Climate and measured movable-asset inequality in standardised regressions

	$\hat{\beta}$	SE	p	R^2
Panel A. Aggregate inequality				
Wealth Gini on PCI (z)	0.0088**	(0.0032)	0.011	0.277
Wealth Gini on rainfall (z)	-0.0020	(0.0032)	0.539	0.015
Wealth gap (T3-T1) on PCI (z)	597.41***	(146.52)	<0.001	0.280
Panel B. Within-tercile inequality				
Within T1 (poorest) on PCI (z)	-0.0789**	(0.0315)	0.019	0.213
Within T2 (middle) on PCI (z)	0.0087**	(0.0041)	0.044	0.075
Within T3 (wealthiest) on PCI (z)	-0.0104**	(0.0043)	0.023	0.170

[Notes] OLS with robust standard errors. Each observation is one year. Dependent variable is the Gini coefficient computed across all households with positive wealth (Panel A) or within the specified wealth tercile (Panel B). PCI and rainfall are standardised to z-scores, so coefficients represent the change in the Gini per one standard deviation of the climate measure. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

recover this exposure because it compresses seasonal timing and omits non-rain conditions, while the PCI carries the commodity channels estimated above. Mean rainfall is nearly identical in low- and high-PCI terciles, at 86.1 and 85.6 rain days respectively, even though predicted commodity values diverge sharply.

The wealth-gap regression gives the level interpretation. A one-standard-deviation increase in the PCI is associated with a 597 *rixdollar* increase in the T3–T1 wealth gap (Panel A, row 3), roughly one quarter of the mean annual gap in the regression sample. The coefficient measures movement in group means, so a higher PCI corresponds to years in which the mean position of the wealthiest tercile moved further away from the mean position of the poorest tercile.

Within wealth groups, high-PCI years follow a different pattern. Inequality falls among the poorest and wealthiest households and rises slightly in the middle tercile. The largest movement is among the poorest households, where a one-standard-deviation PCI increase reduces the within-group Gini by 0.079 points ($p = 0.019$). Since the average within-poor Gini is 0.174, the coefficient is large relative to the usual level of dispersion inside the poorest tercile. The middle-tercile coefficient is positive but small at 0.0087, while the wealthiest-tercile coefficient is negative at -0.0104.

The portfolio evidence explains these signs. The poorest households had very little recorded movable wealth and almost no wine exposure, so the commodity channels driving aggregate gains had little room to separate one poor household from another. Those same gains nevertheless widened the distance between poorer households and the upper tercile. Years favourable to the indexed commodity bundle could therefore compress inequality among poorer settlers while increasing inequality between poor and rich households.

Figure 5 presents the same pattern descriptively by sorting years into PCI terciles. Aggregate wealth inequality rises from 0.649 in low-PCI years to 0.671 in high-PCI years, while inequality among the poorest households falls from 0.290 to 0.108 across the same regimes. The PCI components identify the movement behind this split. Mean wine PCI rises from 252 *rixdollars* in low-PCI years to 388 *rixdollars* in high-PCI years. Wheat moves from -18.9 to 6.8 *rixdollars*, while sheep and cattle move from small negative values to positive values. The movement is concentrated in the commodity profile held higher in the distribution, especially wine.

These two inequality movements can coexist because the aggregate Gini combines distance between groups with dispersion within groups. When high-PCI years lift the rich commodity bundle while leaving poorer portfolios closer to one another, aggregate inequality can rise even as within-poor inequality falls. In the same tercile classification, the mean T3–T1 wealth gap rises from about 1,872 *rixdollars* in adverse years to about 3,401 *rixdollars* in favourable years.

The split between within-group and between-group movement helps explain why the aggregate Gini appears stable over the thirty-year period. Between-group widening and poorest-tercile compression partly offset one another. The level series in Supplementary Fig. 3 makes the between-group movement visible. The T3–T1 wealth gap is strongly associated with the PCI in the unadjusted annual series ($R^2 = 0.28$, $p < 0.001$). The Gini summary alone would miss part of this movement because it folds within-group and between-group changes into one number.

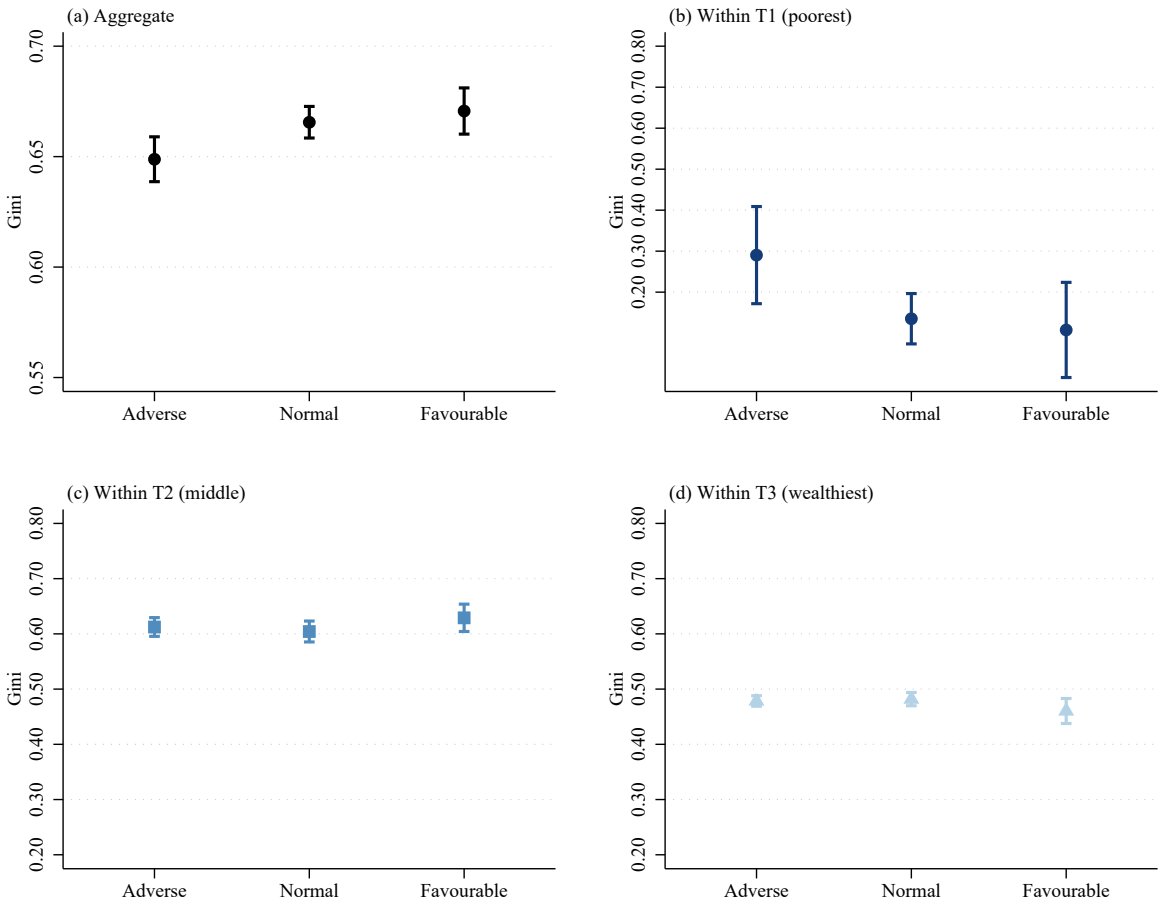


Figure 5: Baseline inequality by climate-impact regime. Years are sorted into terciles by the PCI, interpreted as predicted net production impact (adverse, normal, favourable; 9 years each). Panel (a) shows aggregate wealth Gini. Panels (b)–(d) show within-tercile Gini for the poorest, middle and wealthiest households respectively. Panels (b)–(d) share the same y-axis. Points show group means; error bars show 95% confidence intervals.

Robustness checks identify where the annual association is strongest (Supplementary Table 8). Generated-index checks reproduce the positive Gini coefficient. A parametric first-stage coefficient bootstrap gives a mean rebuilt-PCI coefficient of 0.0087, and a household-cluster full-pipeline bootstrap gives 0.0124 (Supplementary Table 6). A leave-one-year-out PCI remains positively correlated with the in-sample index ($r = 0.79$), while the Gini coefficient becomes smaller and imprecise ($p = 0.138$). Crop-only and no-livestock variants remain positive but weaker, and linear time trends absorb much of the baseline association. Additional diagnostics preserve positive level associations between exposure and inequality,

while distributional variants weaken under trend and period controls and placebo leads predict current inequality (Supplementary Tables 6 and 9). The annual evidence is strongest along the portfolio channel and weaker under aggregate rainfall.

Disasters and annual exposure diverged

We classify a year as extreme when one climate dimension lies more than 2.5 standard deviations from its mean, or when two or more dimensions lie more than 2 standard deviations from their means. By this rule, two years qualify. The first is 1770, driven by autumn rainfall; the second is 1787, driven by cold days. Supplementary Fig. 4 plots the commodity-specific PCI over time.

In monetised terms, both extreme years are positive in net because predicted wine gains outweigh losses in wheat and livestock. Extreme climate frequency and adverse economic exposure diverged in this setting. A year could look extreme in the weather record and still favour the commodity bundle held by wealthier households. The annual wheat, wine and net series are shown in Supplementary Fig. 5.

The two extreme years illustrate the difference between meteorological rarity and distributional exposure. In 1770, unusually high autumn rainfall coincides with predicted losses outside wine, but the wine component is strongly positive at 397 *rixdollars*. The net PCI is 283 *rixdollars*. In 1787, the cold-day count is exceptional. The net PCI reaches 433 *rixdollars* because the wine and cattle components outweigh the wheat loss. These years are extreme in the weather record, yet their net economic sign follows the ownership-weighted commodity profile more than the extremeness of the climate variable alone.

A different pattern appears in 1768, when the narrative record identifies a major flood in Stellenbosch. The flood struck on 30 May, and the *dagregisters* record further flood events in Cape Town later that winter. Yet 1768 falls outside the extreme-year set because the annual count of rain days is near the period mean and no annual climate dimension approaches the threshold. Figure 6 shows production losses around 1768, confirming that rain-day frequency

misses some high-intensity events.

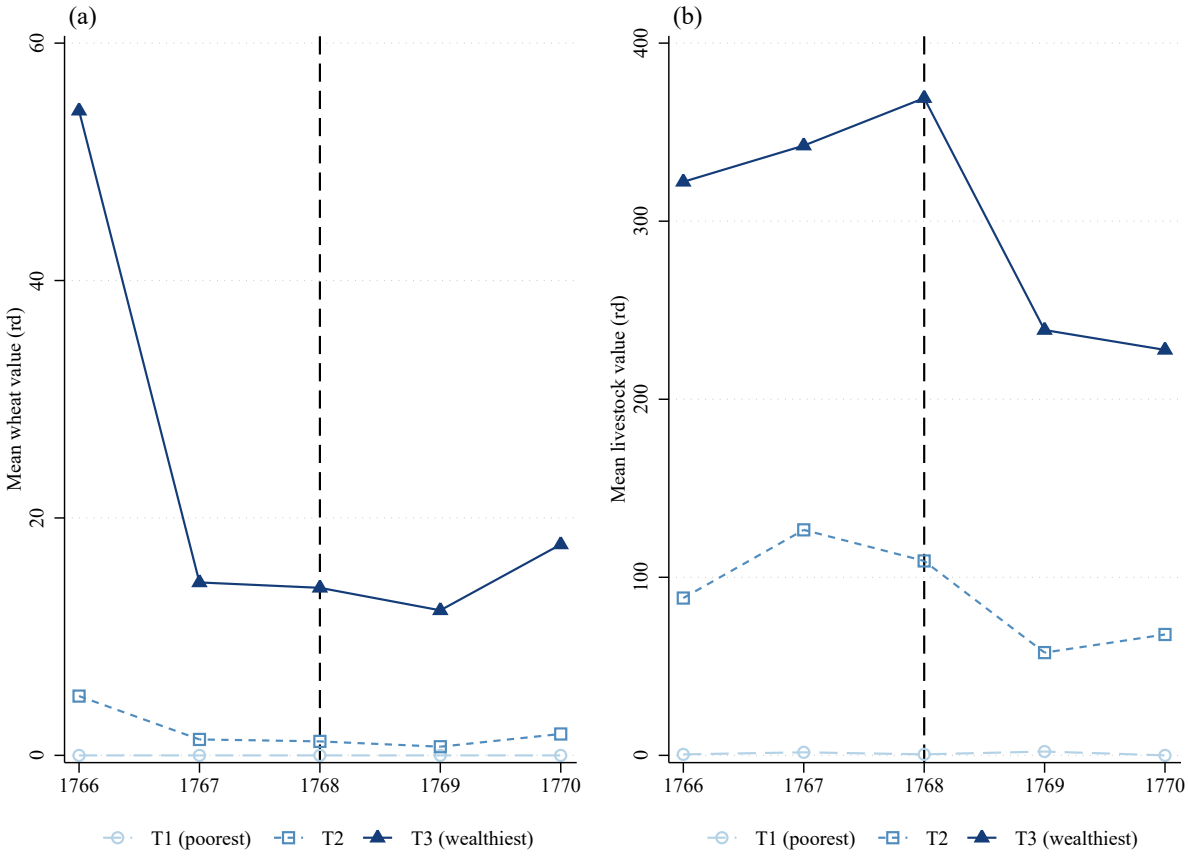


Figure 6: Production values around the 1768 Stellenbosch flood, by wealth tercile. Panel (a) shows wheat value. Panel (b) shows livestock value. Vertical dashed line marks 1768.

The *dagregisters* capture weather frequency better than intensity. They are well suited to systematic seasonal patterns but less able to identify rare, concentrated events such as floods or black frosts. The distinction is useful for climate history. Disaster narratives recover memorable shocks; annual weather series recover repeated exposure profiles that may have stronger implications for production and inequality.

Discussion

This article shows how climate became distributional through the assets households owned before weather arrived. In the eighteenth-century Cape, the same weather profile could

raise the predicted value of one commodity bundle while lowering another because crops and livestock met weather at different points in their production cycles. Because wine was concentrated among wealthier settlers, and because prices give little evidence of systematic compensation for wheat and wine producers, years when the weather profile favoured the commodity bundle held higher in the distribution were also years of wider measured movable-asset inequality. Wealth therefore entered before recovery, helping determine whether weather appeared as loss or gain.

The sign belongs to ownership as much as to weather. At the Cape, high-PCI years were disproportionately wine-friendly and wine was held by rich households; in another agrarian order, the assets favoured by recurring weather profiles could sit lower in the distribution, muting or reversing the inequality effect. The historical case therefore identifies an incidence mechanism, with weather becoming distributional through the ownership structure into which it arrives.

The price evidence tests whether markets displaced the production channel. A crop shortfall can become a higher price paid by consumers, or it can remain with producers as lost output, depending on pass-through. In the Cape price series, wheat and wine provide little evidence of systematic inverse movement with predicted output, consistent with producers tied to VOC demand and a wider colonial market, with no closed local grain or wine market to anchor prices. The estimates leave no evidence of a compensating price response strong enough to erase producer-side exposure.

The 1768 Stellenbosch flood cautions against equating disaster visibility with distributional importance. The best-known disaster in the sample falls outside the aggregate annual climate extremes because monthly rain-day counts capture frequency better than intensity. Narrative archives make dramatic events visible; systematic annual series recover less memorable years in which repeated exposure profiles reshaped production and wealth. Both forms of evidence are needed because they locate different kinds of climate risk.

The linked records place weather, production, prices and household assets in the same

annual frame, allowing climate exposure to be followed before it becomes an outcome. Seasonal conditions can be traced to commodity returns and then to reported movable wealth, giving a household-level account of how weather entered the distribution of assets.

The contemporary relevance lies in the channel itself. Warming changes which weather profiles arrive and how often, but ownership and market pass-through still help determine where their economic sign lands. Studying climate shocks only as aggregate damages misses this allocation problem, because the same realised climate can move households in opposite directions before recovery or adaptation begins.

By linking weather to household assets through production and prices, the paper makes climate inequality observable as a chain of exposure. The aggregate wealth Gini can look stable while weather changes the relative position of households within the distribution, so climate shocks should be studied as reallocations as well as damages.

Methods

Sources and sample

The study links three Dutch East India Company source series for 1760–1791. Daily weather observations from the *dagregisters* provide the climate signal; household-level production records from the Stellenbosch *opgaafrolle* provide portfolios and assets; and colonial estate-auction rolls provide annual price series. The VOC established the Cape of Good Hope settlement in 1652 as a provisioning station for its Asian trade. By the mid-eighteenth century, the Stellenbosch district had become the colony's principal agricultural hinterland and contained most Cape wheat and wine production.[32]

The *opgaafrolle* are annual tax censuses conducted by VOC officials. We use the Stellenbosch district records for 1760–1791, excluding Cape Town. Each entry reports wheat sown and harvested in *muids*, wine in *leaguers*, vines, livestock, enslaved men, women, boys and girls, and settler household members. The census was taken in March, so an entry for year

t records crops harvested before or around March of year t, after a crop cycle that began in calendar year $t-1$. The fiscal origin of the census gives it broad coverage but creates incentives to underreport, especially for wine.[33] Household fixed effects absorb stable underreporting within households. Weather-correlated misreporting would remain a concern if poor and good harvest years were reported differently. The raw panel contains 36,395 household-year observations across 30 census years, with gaps in 1781 and 1783.

We winsorise variables entering the production and wealth measures at the 1st and 99th percentiles, leaving the underlying data untouched. This applies to enslaved men, women, boys and girls, wheat harvested, wheat sown, wine, vines, sheep, cattle and horses. Wheat yield is defined as volume harvested divided by volume sown, with yields above 30 set to missing. Wine yield is wine divided by vines, with yields above 0.1 set to missing. The main estimation sample is restricted to households observed for at least five years, yielding 26,561 observations across 2,109 households with a median panel length of 11 years. Stayer checks use households present by 1770 and still present after 1780. Entrants are systematically poorer than long-present households, consistent with migration dynamics documented in previous work.[34]

The price data are drawn from the Cape Colony's *vendu rollen* (MOOC 10), official records of public estate auctions held under the *Weeskamer* (Orphan Chamber). These auctions record items sold, buyers, and prices in *rixdollars* and *schellingen*.[29] We use the auction records to construct annual valuation benchmarks for enslaved people, cattle, sheep, horses, wheat and wine. For enslaved people we average male and female individual prices using the number of observations as weights. For cattle we likewise use observation-weighted annual means. Sheep, horses, wheat and wine use the annual mean unit price recorded in the cleaned auction summaries. Commodity-year gaps are filled by linear interpolation, with endpoint extrapolation only where the surrounding auction series requires it. The price series is used to value holdings and predicted commodity responses; it is not assumed to describe the sale price received by every producing household. Supplementary Table 10 summarises

the price data.

Climate variables and crop calendars

The *dagregisters* were daily administrative diaries maintained at the Castle of Good Hope in Cape Town. They recorded ship movements, official proceedings and weather, giving a day-by-day series independent of later disaster memory. Previous work extracted daily climate variables for 1773–1791 and extended the approach to earlier Cape records.[27,35] We extend the 1773–1791 record back to 1760, producing monthly counts of rain days, strong-to-gale-force wind days, unusually hot or warm days, and unusually cold or cool days.

The records capture regional conditions approximately 50 km from Stellenbosch. Rainfall is measured as rain-day frequency, with quantities absent from the source. Temperature records are relative to seasonal norms. Wind entries distinguish ordinary conditions from strong-to-gale-force episodes. When at least one month is observed for a hot-day or cold-day series, blank months are coded as zero recorded events. When a year lacks the underlying rain record, blank event counts remain missing. Only 1790 is fully missing after this rule.

Stellenbosch agriculture was shaped by Mediterranean seasonality, VOC demand, and coerced labour. Cool, wet winters from May through August supplied most rainfall. Hot, dry summers exposed farms to south-easterly winds known as the *Cape Doctor*. Wheat was sown in May or June and harvested from late November through February, when dry conditions helped threshing but strong winds threatened standing and cut grain.[36] Wine followed a different calendar. Vines were pruned after vintage and again in winter, entered dormancy during the wettest months, broke bud in September, flowered in October and November, and were harvested in February and March. High winter rain could replenish soil moisture for vines while harming germinating wheat. Strong December and January winds damaged wheat while often bypassing wine.

Because the *opgaafrolle* census was conducted each March,[28] output in year t reflects a crop cycle that straddles years $t-1$ and t. We construct cross-year agronomic variables that

follow the crop calendar (Supplementary Table 1). For wheat, growing rain is May–August of $t-1$, spring rain is September–October of $t-1$, pre-planting autumn rain is March–April of $t-1$, harvest wind and harvest heat combine November–December of $t-1$ with January–February of t, and winter cold is May–August of $t-1$. For wine, winter rain is May–August of $t-1$, spring rain is September–October of $t-1$, summer rain and ripening heat combine November–December of $t-1$ with January–February of t, winter cold is May–August of $t-1$, and vintage wind is February–March of t. Livestock is a stock counted at enumeration, so the livestock equations use contemporaneous calendar-year rain, wind, heat and cold.

Movable wealth and portfolio exposure

The labour regime made exposure unequal. The VOC imported enslaved people from Madagascar, the Mozambique coast, the Indonesian archipelago, and the Indian subcontinent, and drew on indigenous Khoisan labour under often coercive conditions. By the 1770s, approximately three-quarters of settler households in the southwestern Cape owned at least one enslaved person, but slaveholding was highly concentrated.[31,37–39] Wealthier households deployed enslaved labour across ploughing, sowing, vine training, livestock management, cutting, threshing and pressing. The Cape was also part of a wider colonial pattern in which agrarian expansion, labour coercion, and ecological change were mutually reinforcing.[40–44]

We monetise each household's holdings of enslaved people, cattle, sheep and horses at the annual price series described above. The measure captures movable productive wealth and excludes land, buildings, debt, stored crops and the market value of vines. Missing asset components are valued at zero when the underlying count is absent from a household record. Crop output is valued separately and is not included in the wealth measure. Households are classified into wealth terciles based on time-averaged monetised wealth. Cutpoints are computed on one observation per household, so each tercile contains roughly one-third of households. This gives a long-run portfolio position and avoids contemporaneous ranks that respond mechanically to the climate shocks being studied. Supplementary Table 4 reports

descriptive statistics by tercile.

For household climate exposure, the baseline assigns a commodity shock to households that produce or hold that commodity and assigns zero exposure to non-producers and non-holders. Robustness checks replace participation with scale weights. Household-mean weights divide a household's average output or stock by the sample mean among positive holders. Lagged weights use the previous year's output or stock divided by the same positive-holder mean. Fixed pre-period weights use average observed holdings in 1761–1769. These variants distinguish the effect of owning a commodity from the effect of owning it at larger scale.

Exposure framework

Climate affects household inequality when weather changes the value of assets that households own in different amounts. Let a_{ic} denote household i's exposure to commodity c, and let r_{ct} denote the climate-driven value shock to that commodity in year t. The household-level change in value is given by

$$\Delta Y_{it} = \sum_{c} a_{ic} r_{ct}. \tag{1}$$

The distributional direction of a climate year follows from the alignment between commodity shocks and ownership. The covariance between baseline household wealth W_i and the climate-induced value change is

$$\mathrm{Cov}(W_i, \Delta Y_{it}) = \sum_{c} r_{ct} \, \mathrm{Cov}(W_i, a_{ic}). \tag{2}$$

Positive shocks to commodities concentrated among richer households move value upward. Negative shocks to those commodities move value downward. The same logic applies to commodities concentrated lower in the distribution, with the sign reversed. Aggregate output effects and inequality effects can diverge. Aggregate output depends on $\sum_c r_{ct}$, while inequality depends on the match between r_{ct} and $\mathrm{Cov}(W_i, a_{ic})$.

Prices determine how much of a quantity shock remains with producers. For a commodity with output q_{ct} and price p_{ct}, the producer-side value shock can be written as

$$r_{ct} = p_{ct}\Delta q_{ct} + q_{ct}\Delta p_{ct}. \tag{3}$$

An inverse price response can reduce producer exposure when output losses raise prices and output gains lower them. In that case the price term partly offsets the quantity term.

Commodity response models

The production equations estimate how climate changed physical output or stock counts for each commodity. The fixed-effects specification is

$$y_{it} = \boldsymbol{\beta}'\mathbf{X}_t + \alpha_i + \varepsilon_{it} \tag{4}$$

where y_{it} is output of household i in year t, $\mathbf{X}_t$ is the relevant climate vector, α_i is a household fixed effect, and ε_{it} is the error term. Production regressions use producer or holder samples for the relevant commodity and restrict the panel to households observed for at least five years. Standard errors are clustered at the household level throughout, with year-clustered checks reported in Supplementary Table 11. Climate varies at the year level, giving 29 observed climate–household years and 27 complete net-PCI years. All tests are two-sided.

Household fixed effects absorb time-invariant characteristics, including location, soil quality, farm size, managerial ability, and baseline wealth. Identification comes from year-to-year variation in climate conditions combined with the different commodity portfolios held by households.

We estimate Equation (4) using annual rainfall, seasonal rainfall, and the full multivariate specification with rainfall, wind, heat and cold channels aligned to the commodity-specific calendar. The main table reports the full calendar-aligned specification. Wheat uses the six wheat variables described above. Wine uses the six wine variables described above. Sheep

and cattle use winter rain, spring rain, total wind, total hot days and winter cold days in the census year.

For wheat, the reported production estimate is in first differences

$$\Delta y_{it} = \boldsymbol{\beta}' \Delta \mathbf{X}_t + \Delta \varepsilon_{it} \tag{5}$$

which removes time-invariant household differences and uses within-household changes in output and climate exposure. For wine, sheep and cattle, the reported production estimates use household fixed effects. Stayer checks and estimator comparisons are reported in Supplementary Tables 2 and 3.

To test whether climate effects vary across the wealth distribution, we estimate Equation (4) separately by wealth tercile and interact rainfall with log household wealth. The interaction regressions use annual rainfall for wheat, sheep and cattle, and lagged annual rainfall for wine, matching the timing of the wine production cycle.

The interaction specification takes the form

$$y_{it} = \beta_1 X_t + \beta_2 (X_t \times \ln W_i) + \alpha_i + \varepsilon_{it} \tag{6}$$

where W_i is time-averaged household wealth in *rixdollars*. Under this specification, β_2 captures how wealth changes the climate response. We report the implied change in the rainfall response for a doubling of household wealth as $\beta_2 \ln 2$.

We test entry into and exit from production by estimating linear probability models of production participation on the commodity-specific PCI. Because secular trends are strong in crop participation, we estimate fixed-effects models with a linear trend, first differences, and first differences restricted to stayer households.

The stayer restriction also checks whether entry and exit drive the main production results.

Predicted Climate Impact index

The commodity-specific regressions yield estimated climate coefficients for each commodity. We use these to construct a Predicted Climate Impact (PCI) index, the empirical counterpart of r_{ct} in Equation (1). The physical commodity response is

$$\widehat{\Delta q}_{ct} = \sum_{k} \hat{\beta}_{ck} X_{ckt} \tag{7}$$

where $\hat{\beta}_{ck}$ is the estimated coefficient of climate channel k for commodity c, and X_{ckt} is the observed climate value in the calendar used for that commodity. The commodity-specific monetary index is

$$\mathrm{PCI}_{ct} = \bar{p}_c \widehat{\Delta q}_{ct} \tag{8}$$

where $\bar{p}_c$ is the period-mean price from the annual price series. The net PCI sums across commodities, $\mathrm{PCI}_t^{\mathrm{net}} = \sum_c \mathrm{PCI}_{ct}$, capturing opposing signs across commodities in a common unit.

The PCI is a level prediction, so the baseline index uses household fixed-effects coefficients for wheat, wine, sheep and cattle. The wheat coefficients reported in Table 1 are first-differenced estimates because the production result is clearest in year-to-year changes. Supplementary Table 3 compares the wheat estimators, and the FD-based PCI variant is used as a robustness check.

To translate year-level commodity shocks into household exposure, we use portfolio composition

$$\mathrm{Impact}_{it} = \sum_{c} a_{ict} p_{ct} \left(\widehat{\Delta q}_{ct} - \overline{\widehat{\Delta q}_{c}} \right) \tag{9}$$

where a_{ict} is household exposure to commodity c, p_{ct} is the annual price series, and the overbar is the year-weighted mean predicted response for that commodity. Baseline exposure sets $a_{ict} = 1$ for producers or holders and $a_{ict} = 0$ otherwise. Scale-weighted variants replace a_{ict} with household-mean, lagged, or fixed pre-period relative scale weights. Years without

a complete net PCI are set to missing.

Price and inequality regressions

Annual inequality is computed from the household panel after applying the five-year sample restriction. For each year, the movable-wealth Gini is calculated over households with positive monetised movable wealth as $2\,\mathrm{Cov}(R_{it}, W_{it})/(N_t \bar{W}_t)$, where R_{it} is the within-year wealth rank, W_{it} is monetised movable wealth, and N_t is the number of observed households. We compute the aggregate Gini, within-tercile Ginis, and the difference between mean wealth in the wealthiest and poorest terciles.

We test the relationship between the PCI and annual inequality by estimating

$$G_t = \alpha + \gamma Z(\mathrm{PCI}_t^{\mathrm{net}}) + u_t \tag{10}$$

where G_t is the annual inequality outcome and $Z(\mathrm{PCI}_t^{\mathrm{net}})$ is the net PCI standardised across years. The coefficient γ gives the change in the inequality outcome associated with a one-standard-deviation increase in predicted net production impact. The rainfall comparison replaces the PCI with standardised annual rain days. The climate-regime figure sorts years into terciles of the net PCI.

We test price movement by regressing the annual price series on the commodity-specific physical PCI at the year level

$$p_{ct} = \eta_c + \delta \widehat{\Delta q}_{ct} + v_{ct} \tag{11}$$

where p_{ct} is the annual mean price for commodity c. A negative δ indicates inverse price movement because predicted output gains coincide with lower prices and predicted output losses coincide with higher prices. We estimate these regressions with robust standard errors.

Extreme-year definition

We identify extreme climate years using z-score thresholds on seven climate dimensions, covering winter, spring, summer and autumn rainfall, total wind days, total hot days, and total cold days. A year qualifies as extreme if any dimension exceeds ± 2.5 standard deviations, or if two or more dimensions simultaneously exceed ± 2 standard deviations. This definition captures annual frequency profiles. The 1768 Stellenbosch flood is treated separately as a documented event from the *dagregisters* and is used in descriptive flood checks.

Supplementary Fig. 6 displays the climate profile of each extreme year; Supplementary Figs. 7–9 show all observed years.

Data availability

All data required to replicate the results will be deposited in a public repository before publication. Materials are available to editors and reviewers upon request during peer review.

Code availability

All custom code required to reproduce the analysis and figures will be deposited with the replication files before publication and is available to editors and reviewers upon request.

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695 Competing interests

696 The authors declare no competing interests.

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