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Ananya Ashta, UCL Department of Economics

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Foreword

Dear Readers,

Welcome back to Issue 2 of the UCL Journal of Economics.

What an extraordinary year it has been, marked by growth, exploration, and the relentless pursuit of knowledge.

This year, we're delighted to present a series of thought-provoking articles from our peers around the world. It is an honour to announce that we received submissions from four countries - the United States of America, the United Kingdom, Spain, and India. The global reach of our journal is expanding, fostering a truly international dialogue in the field of economics.

We received 30 submissions in total, 11 were selected for peer review, and 8 papers have ultimately been included in issue 2 of the UJE. This speaks to the continuing global reach of the journal and increasing calibre of research we are privileged to showcase in the UJE.

Our journey this year has been marked by transitions and transformations. We welcomed a new editorial board, comprised of undergraduate editors who have demonstrated an unwavering commitment to academic excellence. This team of passionate individuals has not only maintained the high standards set by our inaugural issue but has strived to raise the bar, ensuring that each paper published here is a testament to the pursuit of knowledge and the art of scholarly exploration.

Behind the scenes, our team of 12 diligent peer reviewers worked tirelessly to uphold the rigorous academic standards that define the UJE. Their expertise, commitment, and invaluable feedback have played a pivotal role in shaping the content of this issue.

As I pen this foreword, I am reminded that this is the last time I will have the privilege of addressing you in this capacity. I am truly grateful for the incredible experiences, challenges, and triumphs that this journal has brought into my life. The UJE has truly been a labor of love, and I am deeply thankful for every moment of this journey.

I extend my sincere congratulations to the authors who have contributed to this issue. Your dedication to advancing the field of economics is an inspiration to us all, and I have no doubt that your work will continue to make a meaningful impact.

I would like to give my thanks to Isabelle, Suraj, and Rasmus for not only their efforts and commitment to the journal but also for their friendship and company this last year. I wish the incoming Director, Phin Godfrey, success during his tenure and have no doubt he will raise the journal to new heights.

Our mission of fostering undergraduate research in economics remains as vital as ever, and with each passing issue, we reinforce our commitment to the pursuit of knowledge and discovery.

Thank you, dear readers, for joining us on this incredible journey. As we continue to evolve and grow, I have no doubt that the UJE will remain a beacon of academic excellence and a testament to the incredible potential of undergraduate scholarship.

With heartfelt gratitude and best wishes, I sign off for the last time.

Ananya Ashta

Director, UJE
2022/23

A Note from the New Director

Dear Readers,

I'm incredibly excited to be taking over from Ananya Ashta as the director of the UJE, although she is certainly leaving some big shoes to fill. Having both been founding members of the UJE team, I am very proud of the work Ananya and I have done together and look forward to carrying forward the impact of the UJE for another year.

The team and our submitting authors have worked hard to put together another strong issue. From UCL's Explore Econ conference we have papers on the distributional effect of the UK carbon price floor, outcome bias in European football, and the effects of labour market concentration and worker mobility on wages. The UJE's research fellows have produced papers on the effects of life expectancy on labour productivity in Singapore, and on how market dynamics (e.g., volatility) affect the attention paid by UK retail investors. Our guest submissions include papers on the demand for informal goods in Africa, hospital and physician effects on racial and ethnic disparities in maternal treatment and death, and an application of the Coase theorem to restorative justice.

In the coming year, the team and I will work to ensure that Issue 3 of the UJE meets, and hopefully exceeds, the high standards set by the first two. We will look to expand the reach and impact of the UJE and cement its place so that it can continue delivering on its mission for years to come.

Thank you for your readership and enjoy the issue!

Phin Godfrey

Incoming Director, UJE
2023/24

Explore Econ

Explore Econ is an annual student-run undergraduate research conference organised by the Centre for Teaching and Learning Economics (CTaLE) in UCL's Department of Economics.

The conference showcases the research conducted by students both within and outside the curriculum. This section showcases three prize-winning papers from this year's conference held on 7th June 2023.

https://www.ucl.ac.uk/economics/study/undergraduate/explore-econ-2023

All shortlisted and winning papers and posters can be found on the Explore Econ 2023 website above.

EXPLORE ECON 2023

Article (Explore Econ Winner)

Distributional Effects of the UK Carbon Price Floor

William Nguyen[1]

[1] Student (BSc Economics, 2020-23), Dept. of Economics, UCL, UK; william.nguyen.20@ucl.ac.uk

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Peer review
This article has been peer-reviewed through the journal's standard double-blind peer review, where both the reviewers and authors are anonymised during review

Abstract
This paper empirically investigates the distributional effects of the UK carbon price floor (CPF) on households' electricity expenditure. I employ the difference-in-differences model to analyse the impact of the carbon price floor on vertical inequality. The main result finds that households in the poorest quintile are most impacted by the electricity price increase. I further explore the heterogenous effect on households within the bottom quintile by considering various household characteristics. This paper contributes to the existing literature on carbon pricing policies, in particular their impact on inequality both across income groups and within households in the poorest quintile.

Keywords: Carbon Pricing, Inequality, Expenditure Inequality, Carbon Price Floor (CPF)

1. Introduction

Climate change and inequality are two mainstream issues among economists and politicians. Although the two issues are inextricably linked, few studies and policies are aimed at addressing both issues, particularly in the UK. In this paper, I investigate the distributional impact of the UK carbon price floor (CPF). The CPF is a carbon pricing policy introduced in 2013 consisting of the EU emissions trading system (ETS) and the carbon price support (CPS) which is a carbon tax on producers. The price floor sets a price on carbon of £9/tCO_2. Both components cover the electricity production sector which has consequences for households as the additional cost for producers is passed through to consumer prices. The consensus in the literature is that carbon pricing policies are inherently regressive as carbon- intensive goods such as electricity are necessity goods for which there are no substitutes (Parry, 2004; Nordhaus, 2006; Metcalf, 2009). Hence, this paper explores how the CPF affects electricity expenditure across households, focusing on two forms of inequality: vertical and horizontal inequality. Vertical inequality is defined as the inequality across the income distribution and horizontal inequality is the inequality within the same income range due to various household characteristics.

2. Vertical Inequality

To study the inequality effects of the cost pass-through from the Carbon Pricing Floor (CPF), the Difference-in-Differences (DiD) methodology is employed using data from the UK Living Costs and Food Survey (Oldfield, Banks, and Leicester, 2020). In this paper, the main treatment group is households in the 1st quintile and the control group is households in the 5th quintile.

2.1 Choice of Control Group

Since the carbon price floor is a nationwide policy, finding an adequate control group is challenging. I decided to use households in the 5th quintile (highest) as the control group since they are less affected by the CPF. The reason for this is that richer households have higher price elasticity as they see electricity as less of a necessity good, which makes them more immune to fluctuations in electricity expenditure (Chitnis et al., 2014; Schulte and Heindl, 2017). Furthermore, they have more energy efficient homes meaning they are less affected by electricity price rises (Ministry of Housing, Communities & Local Government, 2014). Thus, in theory, the CPF is expected to have a limited impact on the electricity bills of richer households. A graphical test for the parallel time trend assumption is provided in Figure 1, where it is shown that both the control and treatment groups have similar trends prior to 2013, thereby indicating that the highest quintile is an adequate control group. The lowest quintile is the main treatment group as the poorest households are most vulnerable to changes in electricity prices.

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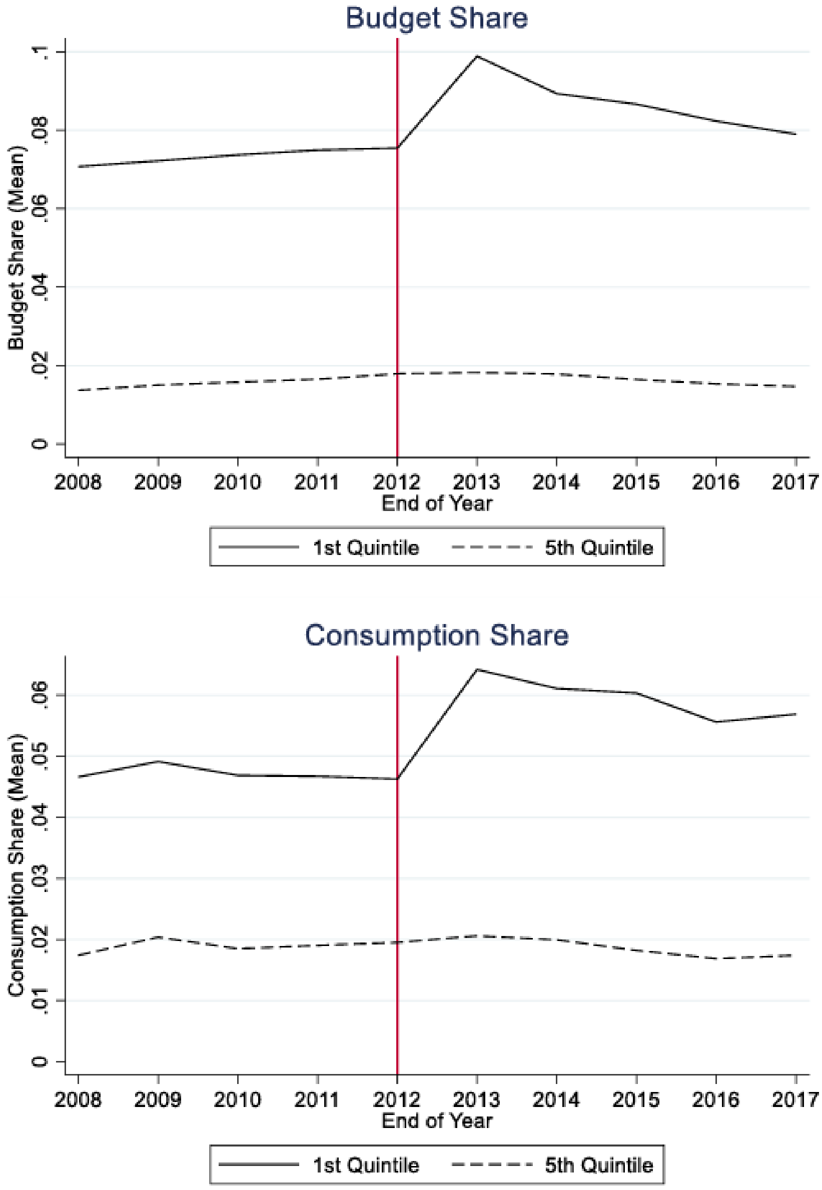

Figure 1: Budget Share and Composition Share

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2.2 Model Specification

The following regressions are estimated:

Budget Share

$$w_{it} = \frac{p_{it}q_{it}}{y_{it}} = \beta_0 + \beta_1 time_t + \beta_2 treated_i + \beta_3 did_{it} + \beta_n X_{it} + \varepsilon_{it} \quad (1)$$

Consumption Share

$$\phi_{it} = \frac{p_{it}q_{it}}{C_{it}} = \beta_0 + \beta_1 time_t + \beta_2 treated_i + \beta_3 did_{it} + \beta_n X_{it} + \varepsilon_{it} \quad (2)$$

where the variables $time_i$ and $treated_i$ are dummy variables and did_i is the interaction term of $time_i$ and $treated_i$. X_{it} represents a vector of control variables and ε_{it} is the error term. This model specification yields the average treatment effect of the carbon price floor.

Budget share and consumption share are chosen as the dependent variables as they reflect the proportion of income spent on electricity. I control for time-varying variables such as the age of the household reference person, household size, employment status, and the number of electrical appliances. I do not control for energy efficiency as this threatens to invalidate the choice of control group, since households in the highest quintile have more energy efficient homes. I also do not control for the geographical location as the Living Costs and Food survey randomises the selection of households chosen each year.

Since the CPF increased yearly from £9/tCO_2 in 2013 to £18/tCO_2 in 2015 (Hirst, 2018), it is also of interest to analyse the yearly effects. In order to decompose the yearly effects between 2013 and 2015, I adapt the staggered difference-in-differences from Abadie (2005) and Callaway and Sant'Anna (2021) which is shown below:

$$y_{it} = \beta_0 + \beta_1 treated_i + \sum_{j=2008}^{2016} \lambda_j year_{t=j} + \sum_{j=2013}^{2015} \delta_j (did_{i,t=j}) + \gamma_n X_{it} + \varepsilon_{it} \quad (3)$$

where $did_{i,t=j}$ is the interaction term of $treated_i$ and $year_{t=j}$. The coefficient δ_j thus represents the estimate of the j-th yearly treatment effect compared to the pre-intervention level. The variable $year_t$ is a dummy variable taking the value 1 if $t = j$ and zero otherwise.

The year dummy for 2017 is omitted to avoid the dummy variable trap. The variable y_{it} represents the dependent variable budget share and consumption share.

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2.3 Results

The electricity budget and consumption share increased for low-income households after the introduction of the carbon price floor in 2013, compared to high-income households as illustrated by Figure 1 and Table 1.

	(1)	(2)	(3)	(4)
	Average Treatment Effect		Yearly Treatment Effect	
VARIABLES	Budget Share	Consumption Share	Budget Share	Consumption Share
time	0.000526	-0.000692**		
	(0.00163)	(0.000330)		
treated	0.0581***	0.0257***	0.0604***	0.0286***
	(0.00128)	(0.000702)	(0.00222)	(0.00187)
did	0.0146***	0.0137***		
	(0.00230)	(0.00109)		
did_2013			0.0186***	0.0132***
			(0.00192)	(0.00198)
did_2014			0.0100***	0.0106***
			(0.00199)	(0.00192)
did_2015			0.0107***	0.0103***
			(0.00200)	(0.00188)
age	-0.000378***	0.000185***	-0.000380***	0.000183***
	(2.85e-05)	(1.98e-05)	(6.17e-05)	(4.04e-05)
unempl	0.0210***	0.0120***	0.0197**	0.0110**
	(0.00475)	(0.00199)	(0.00673)	(0.00403)
elec_app	2.24e-05	-4.82e-05***	2.12e-05	-4.85e-05***
	(1.50e-05)	(6.86e-06)	(1.45e-05)	(7.62e-06)
hhsize	0.00125**	-0.000547***	0.00127	-0.000530
	(0.000486)	(0.000206)	(0.00105)	(0.000520)
Constant	0.0298***	0.0114***	0.0276***	0.00867***
	(0.00189)	(0.00109)	(0.00429)	(0.00167)
Observations	19,741	19,797	19,741	19,797
R-squared	0.161	0.190	0.163	0.189

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table 1: Results from the Difference-in-Differences Regressions

Post-intervention, the average budget share and consumption share increased by 1.46% and 1.37% respectively (Table 4). The carbon price floor incentivised a transition towards cleaner but more expensive electricity which in turn passed through to household energy bills (Castagneto-Gissey et al., 2019). The disproportionate increase in electricity bills for low- income households is consistent with the finding that carbon policies are inherently regressive as UK households in the poorest decile view energy as the second-most important commodity, only after food (Advani et al., 2013).

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It is of note that the increase in the carbon price support from £9/tCO2 to £18/tCO2 in 2015 did not further increase the electricity budget share or consumption share for households in the lowest quintile. The treatment effect in 2014 and 2015 was in fact smaller than the effect in 2013 even though the tax component of the CPF had increased, indicating that the increase in carbon price did not pass through to consumers and did not further increase electricity expenditure shares for the lowest quintile. The further increase in the price of the CPS in 2014 and 2015 had smaller effects on household electricity expenditure since most of the production had already been shifted away from expensive coal-generated power plants.

3. Horizontal Inequality

I next explore the heterogeneity of electricity expenditure across households within the lowest quintile. As observed in the previous section, poorer households spend a large proportion of their income on electricity and the carbon price floor has widened this gap. Hence, any policy that aims to address the disproportionate budget share on low-income households also needs to take into account household characteristics such as age, employment status, and household size. In order to determine the relationship between electricity expenditure and various household characteristics, both before and after the intervention, I use an OLS model with year-fixed effects specified below:

$$Elec_i = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 hhsize_i + \beta_4 unempl_i + \sum_{j=2008}^{2016} \lambda_j year_{i,t=j} + \varepsilon_i \qquad (4)$$

where $Elec_i$ is the household electricity expenditure, $year_t$ is a year dummy, age_i is the age of the household reference person (HRP), $hhsize_i$ is the household size, and $unempl_i$ is a dummy variable taking a value of 1 if the HRP is unemployed and zero otherwise.

Income is controlled for as the sample size is restricted to the 1st quintile. I also estimate the model before the policy (2008-2012) and after (2013-2017) to observe any changes caused by the CPF.

VARIABLES	(1) Electricity Expenditure (2008-2017)	(2) Electricity Expenditure (2008-2012)	(3) Electricity Expenditure (2013-2017)
age	0.165***	0.160***	0.176***
	(0.0334)	(0.0432)	(0.0514)
age2	-0.00217***	-0.00193***	-0.00258***
	(0.000323)	(0.000418)	(0.000500)
hhsize	0.332***	0.499***	0.155
	(0.0626)	(0.0820)	(0.0950)
unempl	-0.888**	-0.897***	-0.327
	(0.280)	(0.325)	(0.484)
Constant	8.728***	8.121***	10.02***
	(0.842)	(1.067)	(1.273)
Observations	7,910	3,973	3,937
R-squared	0.361	0.434	0.331

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Horizontal Inequality Regression Output for Households in the 1st Quantile

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3.1 Results

Table 2 reports that electricity expenditure increases with household size and is higher for unemployed households. This makes sense as larger households and households where people spend more time at home consume more electricity. Moreover, there is a concave relationship between age and electricity expenditure, meaning electricity expenditure increases with age until a certain point where expenditure starts to decrease. This relationship is consistent both before and after the introduction of the CPF in 2013 indicating that the policy had no discriminating effect on age. Figure 2 illustrates that younger and older households consume less electricity compared to households within the age range of 30-49 which have the highest expenditure on electricity which is somewhat surprising as one would expect older people and retirees to spend more time at home thereby consuming more electricity.

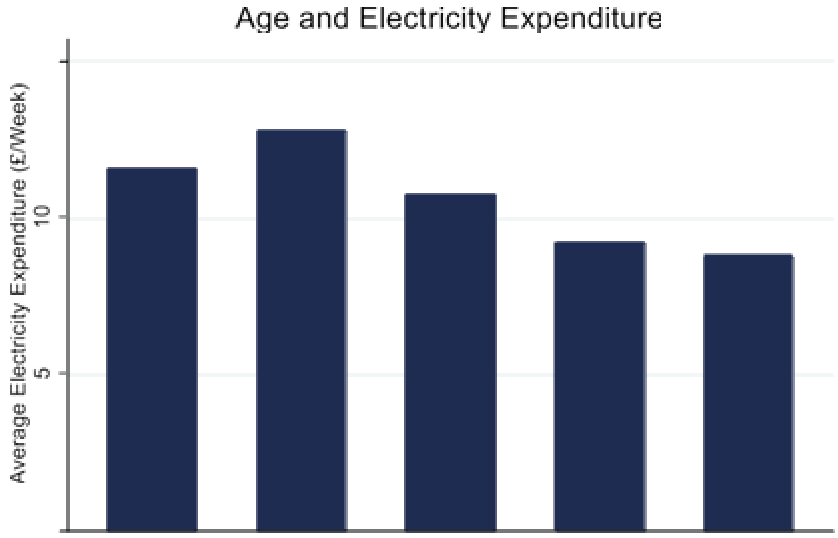

Figure 2: Electricity Expenditure across Age Groups

A possible explanation for this is the permanent income hypothesis, which states that households who expect to earn a higher income in the future will consume more in the present in order to smooth consumption, provided that they are not credit-constrained (Hall, 1978). Households in the lowest quintile can be categorised as either temporarily poor or permanently poor. Thus, households between 30-49 can be thought of as temporarily poor as they expect to maintain an income in the future and hence can consume more electricity.

Older households are permanently poor as they have lower expected lifetime income and hence consume less electricity. Younger households have a high expected lifetime income but may be credit-constrained and hence cannot smooth their consumption (Ortalo-Magné and Rady, 2006). Thus, young households can only afford entry-level homes resulting in lower electricity expenditures.

4. Conclusion

In this paper, I explore the impact of the UK carbon pricing floor on both vertical and horizontal inequality. The main result from this paper is that households in the lowest quintile are most impacted by the electricity price rise, thereby exacerbating vertical inequality, and households between the age range of 30-64 have the highest electricity expenditure. The findings from this paper help inform policymakers on the distributional impacts of carbon pricing policies, which is especially relevant given the current cost of living crisis.

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Article (Explore Econ Popular Vote)

Score! What is it Good for? Why Football Managers Need to Look Beyond Results

Iain Simmons[1]

[1] Student (BSc Economics with a Placement Year, 2019-23), Dept. of Economics, UCL, UK; iain.simmons.19@ucl.ac.uk

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Peer review

This article has been peer-reviewed through the journal's standard double-blind peer review, where both the reviewers and authors are anonymised during review

Abstract

Outcome bias is a pervasive phenomenon in decision-making, referring to the tendency to evaluate decisions made under identical circumstances as more favourable when it results in the desired outcome. This paper analyses this cognitive bias in the context of top-flight European football, examining whether a Bayesian updating model distorted by a multiplicative outcome bias is valid. Managers make significantly more changes to their strategy following a loss than a win, even having controlled for expected performance, in-game performance, and team and game-specific variation. The results of this paper are consistent with a positive-outcome bias, but not necessarily a multiplicative bias.

Keywords: Outcome Bias, Strategy Selection, Behavioural Economics, Cognitive Biases

A Discontinuity Analysis of Outcome Bias in Strategy Selection

Economic agents regularly participate in repeated scenarios (games) that require them to update their beliefs and evaluate their strategies to achieve the best outcomes possible. Following each instance of a game, agents review their strategy selection, assimilating all new information to evaluate if their decision was optimal (Holmstrom, 1979), and if the state of the game has changed. In situations where principals delegate tasks to their subordinates without perfect observation of their actions (principal-agent problems), principals must also update their beliefs on how agents will act, as well as their capabilities. These evaluations motivate principals to persevere with their strategy or adjust to a new optimal choice.

For these evaluations to consistently improve strategies and outcomes, they must be Bayesian, complete and unbiased. Behavioural studies repeatedly find violations of these assumptions, with individuals struggling with quantitative probability problems (Tversky and Kahneman, 1974a), bounded rationality limiting the number of factors that can be considered (Chetty et al., 2009), and heuristics leading to systematic biases in decision-making (Tversky & Kahneman, 1974b).

Whilst outcomes often provide information regarding the correctness of a decision (Hershey & Baron, 1992), individuals tend to evaluate decisions made under identical circumstances as better when the outcome is more favourable (Baron and Hershey, 1988). If individuals repeatedly make suboptimal evaluations, they will make worse decisions in subsequent games, leading to worse outcomes and significant welfare losses. Whilst in everyday situations marginally worse outcomes may be inconveniencing, incorrect assessments of policy and investment decisions can have generational negative impacts at a large cost to taxpayers and shareholders.

Current studies on outcome bias find principals overweight outcomes when rating their agent's decision-making and are unwilling to avoid the bias (Brownback and Kuhn, 2019; König-Kersting et al., 2021) originated in laboratory environments with inexperienced actors completing unfamiliar tasks; a stark contrast to policymakers and business leaders, undermining their findings. Sports provide unprecedented access to elite and well- resourced actors, with well-defined contracts making managers in European football particularly well- incentivised to maximise the probability of winning matches instead of maximising profits (Sloane, 1969; Késenne, 2006; Garcia-del Barrio & Szymanski, 2009). This setting allows for a highly generalisable analysis of the outcome bias, with its finding of a significant outcome bias in managers' strategy adjustments suggesting that the outcome bias is pervasive and likely present in most settings.

Within sports-economics, Lefgren et al. (2015) propose a Bayesian updating model, which focuses on the updating process following a basketball match. Within this setting, they must determine if their strategy selection was optimal ex-ante (state A), having a mean of h or if it was second best (state B), having a mean of l. In both states variance (σ2) is constant. Having observed a performance (P) the coach assesses if their initial assumption that they were in state A (with probability p≥ 0.5) was correct or if they should adjust their beliefs. There is also an additional probability that the state of the world changes (δ ϵ [0 , 0.5]). The performance is assumed to be normally distributed, and the probability of P is as below.

$$Pr(P|A) = \frac{e^{-\left(\frac{1}{2\sigma^2}\right)(P-h)^2}}{\sqrt{2h} * \sigma}$$

$$Pr(P|B) = \frac{e^{-\left(\frac{1}{2\sigma^2}\right)(P-l)^2}}{\sqrt{2h} * \sigma}$$

Using this new information, the manager updates their belief to a posterior belief $\hat{p} = \delta - \frac{p(1-2\delta)}{p+(1-p)e^{-\left(\frac{1}{2\sigma^2}\right)(h-l)(h+l-2p)}}$. If $\hat{p}$ < 0.5, the manager no longer believes they are in state A, and changes strategies.

(Note a team can lose and not see the posterior belief fall below $\hat{p}$=0.5).

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The authors then incorporate a multiplicate outcome bias, suggesting a coach overweighs the likelihood of the outcome occurring by a factor ϒ≥1 (ϒ=1 being the unbiased state). This alters their posterior beliefs to

$\hat{p} = \delta - \frac{p(1-2\delta)}{p\gamma + (1-p)e^{-\left(\frac{1}{2\sigma^2}\right)(h-l)(h+l-2p)}}$ in wins (P>0) and the belief $\hat{p} = \delta - \frac{p(1-2\delta)}{p\gamma + (1-p)e^{-\left(\frac{1}{2\sigma^2}\right)(h-l)(h+l-2p)}}$ in losses.

This model yields 4 key predictions:

Firstly, managers are more likely to adjust strategy in losses than victories, with biased managers more likely to adjust in narrow matches than unbiased managers. This results from losing performances being amplified by ϒ.

Secondly, managers with stronger priors can endure larger losses without switching their strategy.

Thirdly, expected performances have no effect on unbiased managers, but may affect biased managers, as expected losses still reduce their posterior belief.

Finally, unbiased managers only switch strategies in response to events directly related to their strategy, whilst biased managers may respond to other factors. In their paper they used free throw shooting percentage, this paper examines crowd attendances.

In this paper, I test this model using line-up data from 7,965 football games in Europe's 'top-five leagues' (England, France, Germany, Italy and Spain) between 2016 and 2022.

Within their model, the authors exclusively consider score differentials. According to the informativeness principle (Holmstrom, 1979), this is an insufficient model of a manager's adjustment process if outcomes are imperfectly informative of an agent's actions. Within football, scores and past points won are not highly predictive of future results, presenting an R2 value of only 0.253 (Brechot and Flepp, 2020). As such, I adapt the model to incorporate the underlying performance metric expected goals (xG) which is shown to have a higher predictive power of points received in the next ten games (R2 = 0.320) (Brechot and Flepp, 2020). These findings are corroborated within our sample, as shown in the table below where several metrics are regressed against points gained in the next ten games.

Variable	Coef.	St. Error	p-value	R^2
Points in Last 10 Games	0.549	0.009	0.000	0.296
Score Differential in Last 10 Games	0.382	0.006	0.000	0.325
xG Differential in Last 10 Games	0.518	0.007	0.000	0.388

Table 1: Comparison of Predictive Power

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The authors also rarely reference expected results. Betting markets in football are highly calibrated, shown to uphold the efficient market hypothesis (Croxson and Reade, 2014), and are highly accurate in the sample as shown in Figure 1.

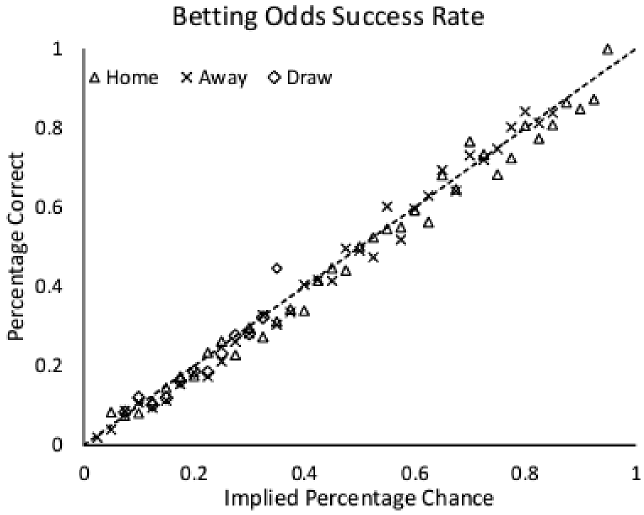

Figure 1: Comparison of implied odds to realised success rate. The dotted line represents perfect predictions, note the strong alignment of the predictions to this line.

Thus, I regress the winning and losing odds against score differentials in the sample to obtain estimates for the ex-ante predicted score differential for each game (draws are possible so there is no perfect collinearity).

Score Differential	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Win Probability	3.574	.308	11.62	0	2.971	4.177	***
Loss Probability	-1.423	.338	-4.21	0	-2.086	-.76	***
Constant	-.825	.239	-3.45	.001	-1.293	-.356	***

Mean dependent var	0.306	SD dependent var	1.849
R-squared	0.239	Number of obs	10855
F-test	1703.644	Prob > F	0.000

**** p<.01, ** p<.05, * p<.1*

Table 2: Calibration of Predicted Score Lines from Implied Win Probabilities

To test the predictions, I formally run the regression below.

$$\begin{aligned} UnmandatedChanges_{i,g+1} &= \beta_0 + \beta_1 Win_{i,g} + \beta_2 Loss_{i,g} + \beta_3 PD_{i,g} + \beta_4 PD_{i,g} * Loss_{i,g} + \beta_5 UnexpectedSD_{i,g} \\ &+ \beta_6 UnexpectedSD_{i,g} * Loss_{i,g} + \beta_7 UnexpectedXG_{i,g} + \beta_8 UnexpectedXG_{i,g} \\ &* Loss_{i,g} + \varepsilon_{i,g+1} \end{aligned}$$

Here i indexes the team and g indexes the game during the season, $UC_{i,g+1}$ are the number of changes a manager makes to their line-up in the subsequent game excluding suspensions and injuries picked up in and between games, $UnexpectedSD_{i,g}$ is the score differential between the reference team i and their opponent in game g minus the predicted scoreline, $Win_{i,g}$ is an indicator variable with a value of 1 if the reference team won the match and 0 otherwise, $Loss_{i,g}$ is an indicator variable with a value of 1 if the reference team lost the match and 0 otherwise, $PDI_{i,g}$ is the score differential implied by the market average betting odds, $UnexpectedXG_{i,g}$ is the xG differential minus the predicted scoreline, and $\varepsilon_{i,g+1}$ is the error term.

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Score differential terms should have negative coefficients, as winning makes you less likely to make changes, and the predicted differential should have insignificant results. Table 3 shows the results.

	Unmandated Changes
Win	-.292***
	(.043)
Loss	.233***
	(.043)
Predicted Differential	.159***
	(.027)
PD * Loss	-.218***
	(.034)
Unexpected Score Differential	-.092***
	(.018)
Unexpected SD * Loss	-.079***
	(.026)
Unexpected xG Differential	-.104***
	(.016)
Unexpected xG * Loss	.014
	(.025)
Points in Last 5 Games	-.077
	(.068)
Team Controls	Yes
Game-specific Controls	Yes
Mean Changes	2.236
Observations	15910
R-squared	.265

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 3: Regression Results

The outcome variables are both significant, with wins being associated with 0.292 fewer changes, and losses with 0.233 more changes. In losses, the predicted scoreline has a net-negative coefficient, suggesting that managers are biased. Finally, whilst xG has a constant coefficient in wins and losses (rational behaviour), as the score differential gains additional weight in losses, the relative weight of performances falls in losses, potentially suggesting that the less salient metric (performance) loses weight in losses.

Overall, having considered data from the most-skilled football managers, these results are highly generalisable, suggesting that principals become overconfident in positive outcomes, and should extend a greater level of scrutiny to all results. Increased data collection on efforts and performances alone is not a panacea, as this data is of little use if it is not considered accurately. The results indicate that avoiding the common wisdom to 'not fix what isn't broken' is crucial to success, whilst encouraging a broader range of opinions and possible solutions in suboptimal outcomes is desirable. It truly is not the end result that matters, but how we get there that makes all the difference.

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Article (Explore Econ Winner of the Stone Centre Prize)

Labour Market Concentration and Worker Mobility: Evidence from Online Vacancies

Matias Makiranta[1]

[1] Student (BSc Economics, 2020-23), Dept. of Economics, UCL, UK; matias.makiranta.20@ucl.ac.uk

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Abstract

This paper uses big data on German online vacancies to investigate the impact of local labour market concentration on wages. Herfindahl-Hirschman Indexes are calculated based on the number of vacancies posted by firms in geographic-occupational labour markets. Based on IV results, a 1% increase in labour market concentration decreases posted wages for full-time employees by 0.098%. Workers who can work remotely do not face negative wage effects from labour market concentration suggesting that worker mobility can mitigate the negative wage effects of labour market concentration. While most vacancies occur in competitive labour markets, rural areas exhibit notable concentration.

Keywords: Labour Market Concentration, Herfindahl-Hirschman Index, Rural-Urban Wage Gap, Remote Work, Worker Mobility

1. Introduction

This article builds on an oligopsony model by Boal & Ransom (1997), which predicts that wages decrease as labour market concentration increases. With an upward-sloping labour supply, the decrease in wages reduces employment and labour market concentration causes deadweight loss. We estimate labour market concentration with online vacancy data from Germany and investigate the impact of local labour market concentration on wages.

The wage effects of labour market concentration have been studied earlier, but this is the first paper to also study the heterogenous effect of labour market concentration between remote and non-remote workers. In theory, remote workers should not be affected by local labour market concentration because they are mobile and can move to other labour markets. Our objective is to test whether increasing remote work or worker mobility could be a successful policy response for labour market concentration.

Most studies calculate Herfindahl-Hirschman indexes (HHI) for labour market concentration based on the employment share of each firm in geographic-occupational labour markets (e.g. Abel, et al., 2018; Bassanini et al., 2022; Benmelech et al., 2022; Rinz, 2022). We use vacancy shares instead, because we consider vacancies to be a better measure of workers' outside options. When negotiating for wages, the bargaining power of workers is increased only if there are vacancies available as alternatives and employment shares may underestimate concentration if jobs are not vacated frequently. Vacancy-based analyses with US data find large negative wage effects from labour market concentration (Azar et al., 2020; Azar et al., 2022) and this paper investigates whether a similar effect exists in a European country with different labour market institutions than US.

2. Estimating Labour Market Concentration

2.1 Data

Our near-universe dataset from Eurostat Web Intelligence Hub (Appendix-1) covers all vacancies posted online in Germany during 2020. It includes approximately 7.3 million postings with information on education and experience requirements along with over 50 other variables. Posted wage is available for 12.5% of the postings and we use wage data for full- time employees with unlimited contracts because we have data only on annual wages.

2.2 Herfindahl-Hirschman Index (HHI)

We estimate labour market concentration with HHI, calculated based on the number of vacancies posted by firms in geographic-occupational labour markets.

$$HHI_{m,q} = \sum_{j=1}^{J} s_{j,m,q}^{2}.$$

.

The variable s is the share of vacancies expressed as a number between 0 to 100 that firm j has in market m during a quarter q. A single labour market is defined as all workers within a 3- digit ESCO occupation classification inside a NUTS-3 region (ESCO, 2022; Eurostat, 2023). For 37.6% of vacancies, the dataset does not include the name of the posting company. We assume that vacancies with a missing company name are posted by different individual firms, and thus our estimates provide a lower-bound for labour market concentration. Azar et al. (2022) use the same assumption with online data from the US.

The median vacancy is posted in a competitive labour market ($HHI \approx 168$) but labour markets in rural areas can be especially concentrated.

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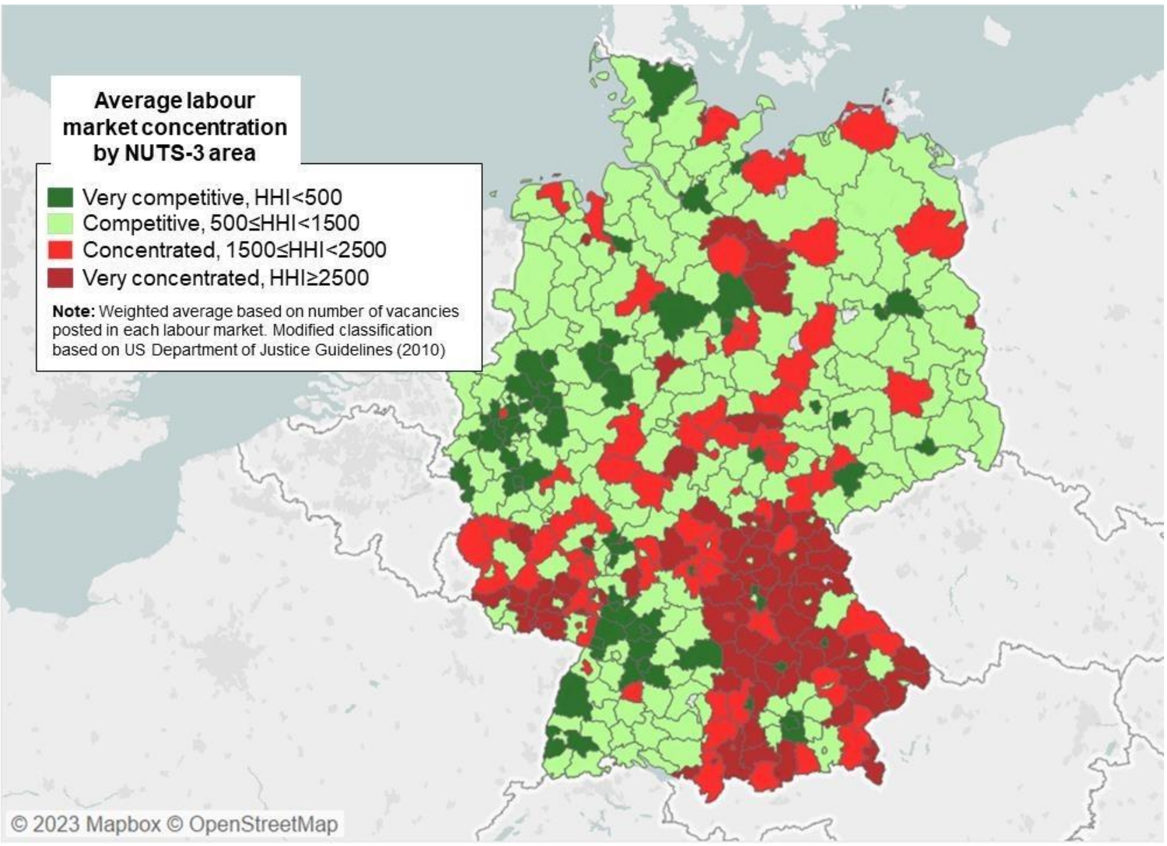

3. Results

3.1 Wage Effects

In our main specification, vector X includes all controls and β measures the elasticity of posted wages (w) with respect to HHI.

$$\log w = \alpha + \beta \times \log HHI + \gamma_i^T X$$

The relationship between labour market concentration and wages is causal only if labour supply and total market demand are held constant (Boal & Ransom, 1997). In a simplified model, total market demand depends on the value of marginal product, which is a function of labour productivity and output market price.

We first use OLS, and proxy for labour productivity with education and experience controls, while occupation and area fixed effects control for labour supply. This implies no statistically significant effect (Table-1), but there are multiple reasons to believe that this result is biased.

Firstly, there might be market-level, time-varying labour supply and demand effects. For example, the labour supply within a specific labour market might become constrained within some period, which would increase wages because the firms must compete over employees. This could lead us to falsely conclude that labour market concentration has no impact on wages, because labour supply is more likely to become constrained in concentrated labour markets within rural areas. Secondly, wages could be influenced by time-varying firm specific effects. Finally, firms may choose to post wages online only for specific types of vacancies (e.g. mainly for low-wage workers).

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Thus, we instrument HHI using the leave-one-out instrument (LOO), which predicts local labour market concentration based on the likely concentration in other markets within the same occupation. Specifically, we instrument log$HHIo,g,q$ with the average of $log\left(\frac{1}{N_{o,g',q}}\right)$ where $N_{o,g',q}$ is the number of firms who posted a vacancy in all other geographical areas g' within the same occupation o and quarter q. The instrument is commonly used (e.g., Azar et al. 2022; Bassanini et al., 2022; Rinz, 2022) and is likely uncorrelated with the three main factors – labour productivity, product market price and labour supply – identified here as influencing wages. First-stage regression shows that the instrument is strong with a t-statistic of 76.24 (Table-2). Based on the main IV estimate, a 1% increase in labour market concentration decreases posted wages for full-time employees by 0.098% (Table-1, column 2). This is in line with our expectation that OLS underestimates the impact of labour market concentration on wages. Moving from the median (HHI≈168) to a highly concentrated market (HHI=2500) decreases wages by 23.25%.[1] The main threat to identification is that productivity shocks to occupations could be correlated across areas. In IV specifications, we can't control for occupation fixed effects because this is the level at which our instrument is defined at (Azar et al., 2022). For example, a national level decline in the productivity of some occupation would increase concentration and decrease wages in most labour markets within that occupation. The instrument protects against spurious correlation between concentration and outcomes that is due to local changes in productivity, but not against national-level changes in productivity that influence both concentration and other labour market outcomes.

Table-1: Main results

	(1) OLS	(2) IV	(3) IV
VARIABLES	Log Wages	Log Wages	Log Wages
Log HHI	0.0165	-0.0981***	-0.101***
	(0.0183)	(0.0190)	(0.0190)
Remote × Log HHI			0.145***
			(0.0410)
Remote			-0.746***
			(0.187)
Fixed effects	Area & Occupation	Area	Area
Other control variables	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter
Instruments	None	LOO	LOO, LOO×Remote
Observations	11,603	11,603	11,603
R-squared	0.176	0.131	0.124

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[1] Wages change by (ln(2500)−ln (168))×(−0.098)=−0.264… log-points, which translates to ($e^{-0.264\ldots}$− 1)×100% ≈ −23.25 %

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Table-2: First-stage regressions

VARIABLES	(1) Log HHI	(2) Log HHI	(3) Remote × Log HHI
LOO	0.581***	0.603***	-0.0481***
	(76.24)	(78.02)	(-6.563)
Remote × LOO		0.222***	0.734***
		(12.74)	(26.81)
Remote		1.399***	11.12***
		(8.669)	(44.28)
Fixed effects	N/A	Area & Occupation	Area
Other control variables	Education, experience	Education, experience, quarter	Education, experience, quarter
Observations	11,603	11,603	11,603
R-squared	0.831	0.867	0.915

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2 Wage Effects for Remote Workers

Appendix-2 lists occupations, such as developers and sales staff, in which there were likely remote work opportunities available during the pandemic year of 2020. We define a binary variable $remote$, which equals 1 if the vacancy is for any of these occupations. We add $remote$ and the interaction term log HHI × $remote$ to our earlier specification.

$$\log w = \alpha + \beta \times \log HHI + \mu \times \log HHI \times remote + \delta \times remote + \gamma_i^T X$$

The elasticity of wages on HHI for remote workers is β + µ. We continue to instrument log- HHI with the leave-one-out instrument (LOO) while the interaction term is instrumented with LOO × $Remote$. Arguments for exogeneity remain the same as earlier, and instruments are strong based on first-stage regressions (Table-2).

Workers with remote work opportunities do not face negative wage effects for local labour market concentration, and the estimated coefficient for remote workers is even positive, although moderately small in magnitude (Table-1, column 3). In this specification the wage effect for other workers is also slightly larger than estimated earlier.

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3.3 Robustness Checks

Top-Coding

Wages are top-coded with a maximum annual wage of €90000 and we estimate specifications from Table-1 also with Tobit models. The estimated coefficients are almost identical to the ones found earlier, which suggests that top-coding is unlikely to influence our results. This is expected because only 5.72% of the wage offers are above €90000.

Table-3: Tobit estimates

VARIABLES	(1) Tobit Log Wages	(2) IV-Tobit Log Wages	(3) IV-Tobit Log Wages
Log HHI	0.0139	-0.0949***	-0.0978***
	(0.0182)	(0.0182)	(0.0182)
Remote × Log HHI			0.146***
			(0.0399)
Remote			-0.747***
			(0.182)
Fixed effects	Area & Occupation	Area	Area
Other control variables	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter
Instruments	None	LOO	LOO, LOO×Remote
Observations	11,603	11,603	11,603

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Spillover Effects

We use relatively small NUTS-3 areas as the boundaries for our labour markets because studies show that the attractiveness of jobs to applicants sharply declines with distance (Manning & Petrongolo, 2017; Marinescu & Rathelot, 2018). However, with the small NUTS-3 areas workers might be able to switch away from a concentrated market to a less concentrated one, which reduces labour supply in the concentrated market and increases supply in the less concentrated one. This causes an increase in wages in the concentrated market and a decrease in wages in the other one, which might lead us to underestimate the impact of labour market concentration. Because of these potential spillovers, we conduct alternative specifications in which we define single labour markets based on the larger NUTS-1 and NUTS-2 areas. The main results remain the same, although the estimated wage effect from local labour market concentration is slightly larger in magnitude.

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Table-4: Alternative definitions for local labour markets

	(1) IV	(2) IV	(3) IV	(4) IV
VARIABLES	Log Wages	Log Wages	Log Wages	Log Wages
Log HHI	-0.146***	-0.121***	-0.159***	-0.131***
	(0.0212)	(0.0195)	(0.0217)	(0.0200)
Remote × Log HHI			0.205***	0.173***
			(0.0466)	(0.0406)
Remote			-0.757***	-0.731***
			(0.142)	(0.145)
Fixed effects	Area	Area	Area	Area
Other control variables	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter
Instruments	LOO	LOO	LOO, LOO×Remote	LOO, LOO×Remote
Definition of a single labour market	3-digit occupations within NUTS-1 areas	3-digit occupations within NUTS-2 areas	3-digit occupations within NUTS-1 areas	3-digit occupations within NUTS-2 areas
Observations	11,603	11,603	11,603	11,603
R-squared	0.033	0.054	0.050	0.124

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4. Conclusion

Based on IV results, a 1% increase in labour market concentration decreases posted wages for full-time employees by 0.098% in Germany. The median labour market in Germany is competitive, but labour market concentration can cause significant downward pressure on wages in rural areas, potentially causing a wage gap between rural and urban workers and thus contributing to wage inequality.

Workers who can work remotely do not face negative wage effects from labour market concentration. This suggests that supporting labour mobility and remote work can potentially mitigate the negative effects of labour market concentration. Example policies include worker mobility schemes (e.g. EURES, 2023) or legislation which gives employees the right to request remote work (Gov.ie, 2022). As a large employer in many countries, the public sector can also ensure as many remote work opportunities as possible. A more realistic explanation is that most Rohingya worked in farms and fisheries in Myanmar, and thus have limited ability to influence wages in Chittagong, where these sectors are not very large or well-established (Rakhine Commission, 2017). Recall the literature review's allusion to the relation between skill-substitutability and wage-impacts of refugees.

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Research Fellows

This year, the research division of the Economic Tribune, the official magazine of the UCL Economics department, enlisted a team of undergraduate students to undertake a one-year research project with the aim of submitting their paper to the UJE.

The following section exhibits original, high quality research output from two dedicated UCL students working in collaboration with the research division of the Economic Tribune and the UJE.

As with all papers in this journal, their work has been edited and double-blind peer reviewed to a high standard.

THE ECONOMIC TRIBUNE

Article

Returns to Longevity? The Effects of Life Expectancy on Labour Productivity in Singapore

Wei Yang Shaun Ng[1]

[1] Student (BSc Economics, 2021-24), Dept. of Economics, UCL, UK; shaun.ng.21@ucl.ac.uk

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Peer review

This article has been peer-reviewed through the journal's standard double-blind peer review, where both the reviewers and authors are anonymised during review

Abstract

While Singapore has consistently been at the forefront of global rankings when it comes to life expectancy and labour productivity, their relationship and interconnectedness are widely contentious. This paper attempts to specifically analyse whether life expectancy affects labour productivity through an instrumental variable approach using 2-Stage-Least-Sqaures (2SLS) regressions. I analyse the effects of life expectancy on labour productivity through multiple channels - education, savings, and the interaction between Malthusian effects and demographic transitions. While further controls must be considered to establish causality, this paper shows a positive association between life expectancy and labour productivity, shedding light that policy investments in health outcomes extend beyond demographic risk management to one which contemporaneously strengthens labour productivity.

Keywords: IV, Life Expectancy, Labour Productivity, Population Demographic

1. Introduction

> *"Health is both a pre-condition of productivity and also an outcome of productivity."*
> *- Civil Service College Singapore*

Lee Kuan Yew, Singapore's revered founding father once said, "our most valuable asset is in the ability of our people". An island state without any natural resource endowments, Singapore's key driver of growth has been human capital. Singapore's committed pursuit of productivity is evidenced in the establishment of various government institutions dedicated to raising productivity, such as the National Productivity Board in 1972, Productivity and Innovation Board in 2002, and Future Economy Council in 2017.

Singapore's life expectancy has experienced tremendous growth from an average of 65.7 years in 1960 to 83.5 years in 2019, the 4th highest life expectancy globally in 2019. Furthermore, global organisations such as the United Nations and World Bank predict that this rising life expectancy trend in Singapore is likely to persist for the next few decades. Concurrently, Singapore experienced significant labour productivity gains as evidenced from its output per hour soaring from a measly \$3.90 to \$54.55.

This paper attempts to explore the contribution of demographic and health factors, specifically life expectancy, as a driver of labour productivity. While Singapore's rapid productivity growth have often been attributed to the confluence of successful policymaking, strategic geographical location and political stability, it remains pertinent to scrutinize the linkages between life expectancy and labour productivity.

While there is extensive economic literature on the relationships between life expectancy and economic growth, and that of ageing and labour productivity, there have been relatively fewer studies examining the effects of life expectancy on labour productivity. Notwithstanding, these studies shed light on the effects of demographic factors on economic output, albeit with arguably inconsistent findings. Acemoglu and Johnson (2007) find that health effects have a nonsignificant effect on income growth and that life expectancy and economic growth are negatively related. This contrasts with a study by Ashraf et al (2008) which establishes that life expectancy is positively associated with economic growth. Additionally, some studies posit an inverted U-shape relationship between life expectancy and economic output (Cervellati & Sunde, 2011).

Empirical data postulates that countries with elevated economic output generally exhibit higher labour productivity levels. Nevertheless, this relationship varies among countries, even those with comparable GDP per capita as delineated in Figure 1. Consequently, although studies exploring economic growth provide insight into the interplay between increased life expectancy and output performance, the relationship between growth and productivity itself remains difficult to estimate. Singapore is observed to exhibit higher labour productivity in terms of output per hour worked as compared to countries with similar GDP per capita levels. This motivates the direct analysis of life expectancy on labour productivity in the unique context of Singapore.

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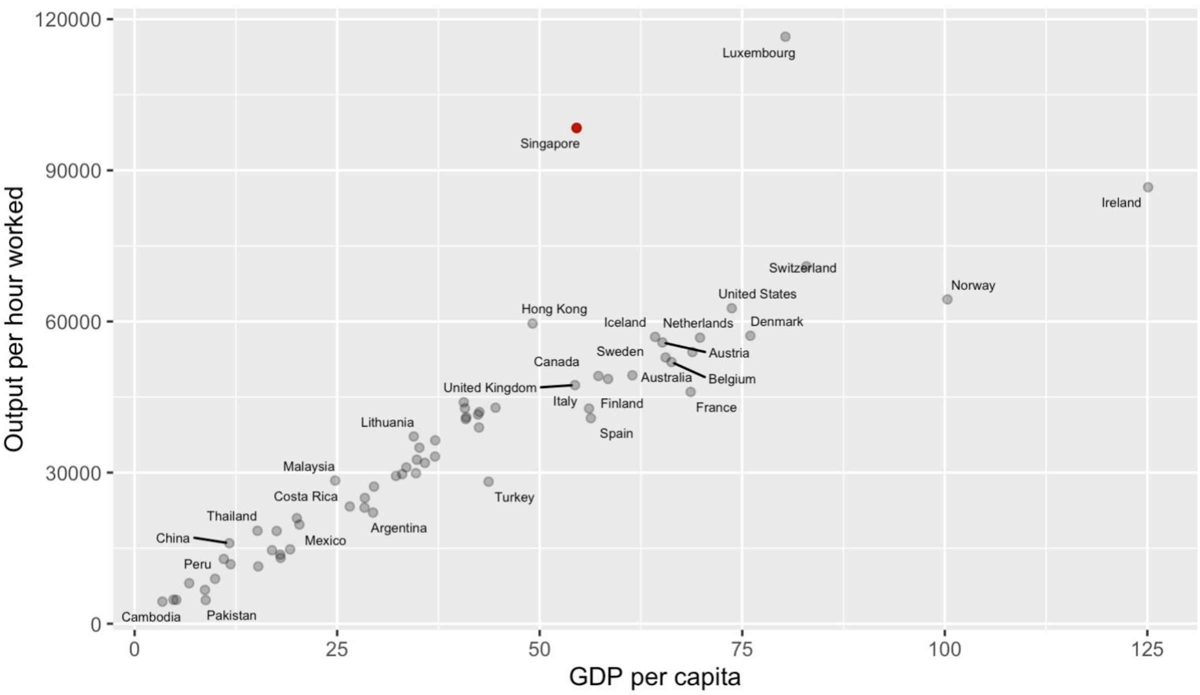

Figure 1: Output per hour worked in international $ in 2017 prices per hour (Penn World Table) vs GDP per capita (World Development Indicators)

Theoretically, the effect of life expectancy on labour productivity remains ambiguous due to opposing dynamics. Life expectancy is expected to increase the returns to education which boosts education attainment's effect on years in the labour force which raises incentives for higher education, thereby raising labour productivity (Kalemli et al 2000). Furthermore, higher expected life expectancy leads to an increased capital stock of the economy which enhances capital deepening and boosts labour productivity (Dua and Garg, 2019). However, in the presence of Malthusian effects, an increase in life expectancy increases population growth, which consequently reduces growth in income per capita.

This paper contributes to the existing literature by exploring the relationship between life expectancy and labour productivity in the context of Singapore and uses a two-stage least-squares statistical model in attempting to address problems of endogeneity stemming from the reverse causation of labour productivity on life expectancy. While this paper acknowledges that the relationship between life expectancy and labour productivity is likely to be casually related in both directions and that simultaneity is likely to persist, it only attempts to examine specifically the direction of the effects of life expectancy on labour productivity.

Data in this paper is limited from 1961-2019 to exclude the effects of a Circuit Breaker in Singapore as a 2020 Covid-19 response whereby physical workspaces were forced to close and work-from-home practices were mandated. The Circuit Breaker resulted in an aggregate decrease in working hours, which invariably affects labour productivity performance.

2. Literature Review

2.1 Life Expectancy and Labour Productivity

Life expectancies in this study are taken as the expected life expectancy at birth in years as detailed in the World Development Indicators. While many studies have focused on GDP per capita as a measure of economic output and a productivity measure, this paper uses real output per hour worked as a measure of productivity. This choice of productivity specifically captures the effects of life expectancy on labour productivity for the workforce instead of the general population. Life expectancy is expected to be positively correlated with ageing which raises the pool of retired individuals which acts as a drag on GDP per capita (Oliveira Martins et al., 2005). However, wider economic literature remains divided on the effect of ageing on labour productivity across regions and sectors. In addition, real output per hour worked is used instead of real output per worker to include part-time workers and variations in hours of full-time workers across the business cycle. In the context of Singapore,

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labour productivity exhibits a high correlation with the real GDP, displaying highly procyclic nature. This is attributable to the firm's behaviour over the business cycle where firms are reluctant to hire or shed workers during booms and recessions but rather adjust their factor utilisation rates (Kuan, 2022). As such, accounting for the procyclicality of labour productivity, labour productivity should be observed over longer time periods to reflect changes across various business cycles. This paper analyses the data from 1961 to 2019, capturing labour productivity performance over multiple business cycles.

2.2 Linkages between Life expectancy and Productivity

The Education Channel

Life expectancy raises incentives for education investment which increases the level of educational attainment of workers (Cervellati and Sunde 2013). Longer life expectancy boosts education attainment's effect on the increased years in the labour force, encouraging higher uptake of education. A study by World Bank (2020) further revealed that for every additional increase of 8.3 years of life expectancy, individuals undertake one additional year of education. As the level of educational attainment of workers increases, the stock of skilled professionals in the country increases which promotes complements with complex machinery and technologies, pertinent to jobs in knowledge-based economies (Annabi, 2017). There is wide consensus in economic literature that schooling and skills training has a positive effect on the marginal product of labour and the output produced per unit of labour, reflecting labour productivity gains. Furthermore, research evidence suggests that higher education attainment indeed raises productivity rather than a signalling ability (Chevalier et al., 2004).

Beyond the effect of raising the quality of human capital, the education channel affects labour productivity through its negative effect on the fertility rate (Cervellati and Sunde, 2011). As the returns to education increase with higher life expectancy, the incentive to have children decreases. Females who have additional years of schooling are more inclined to pursue professional careers which delays the decision of having children, as outlined by Martin, (1995). Ashraf (2013) further asserts that the decreased fertility rate is then expected to raise aggregate productivity through the "childcare effect" as parents have a greater stock of time that can be devoted to labour.

The Savings Channel

As life expectancy increases, the level of precautionary savings is expected to increase as workers save a larger proportion of income for retirement. Bloom et al. (2003) find that the increase in life expectancy leads to higher savings rates at every age. Similarly, a study by Sheshinski (2006) reveals that while aggregate steady-state savings rises with higher levels of life expectancy, the age distribution and elasticity of optimum retirement to longevity both determine the extent of this savings increase. While Singapore has a compulsory savings and pension scheme, the "Central Provident Fund" (CPF) that involves the co-savings of both employee and employer, where the percentage of the salary as the employer's share declines as the employee ages. As such, we would expect that employees will increase their discretionary savings for retirement if they forecast a higher life expectancy, as outlined earlier. Famously, the classic Solow growth model posits that the increase in savings results in greater investment, which increases the capital stock in the economy. This accumulation of capital stock contributes to "capital deepening", whereby the proportion of capital stock to the number of labour hours increases. A growth accounting framework analysis by the Ministry of Trade and Industry Singapore (MTI) finds that increases in capital intensity contributed approximately 2.2 percentage points of labour productivity for growth in Singapore from 2009 to 2019.

Malthusian Effects and Demographic Transition

Famously, the Malthusian growth models predict that an increase in life expectancy increases population growth, depressing capital-to-labour and land-to-labour ratios, hence reducing the marginal product of labour. While a seminal study by Acemoglu and Johnson (2007) finds that a 1 percentage point increase in life expectancy is associated with a 1.7 - 2 percentage point increase in population, Cervellati and Sunde (2011) assert the importance of a demographic transition in predicting the relationship between life expectancy and population growth. Referencing their model, Singapore is well characterised to have undergone the demographic transition given that life expectancy in Singapore has well risen above 50 with consistently declining fertility rates. Given the negative correlation between life expectancy and population growth observed in Singapore, the negative effects of life expectancy on productivity in the Malthusian model are immaterial, regardless of the mechanism behind the demographic transition under the hypothesis of Cervellati and Sunde (2011).

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3. Methodology

While this paper analyses the effect of life expectancy on labour productivity, the reverse is likewise possible. Addressing endogeneity stemming from reverse casualty and guided by the empirical neoclassical growth specification model used by Acemoglu and Johnson (2007) in their estimation of the causal effect of life expectancy on income per capita, this paper employs a two-stage-least-squares (2SLS) to estimate the effect of life expectancy on labour productivity.

Model:

Regression Specification:	
$log(Y_t) = \beta_0 + \delta_t \boldsymbol{X}_t + \beta_1 log(LifeExp_t) + \epsilon,$	
Y_t	Output per hour worked ($/hour, inflation-adjusted)
$\boldsymbol{X}_t$	Vector of control variables, including: ● Trade Openness (Trade as % of GDP) ● Young Age Dependency Ratio (ratio of $\frac{Population\ age\ \leqslant 15}{Population\ age\ 15-64}$) ● Old Age Dependency Ratio(ratio of $\frac{Population\ age\ >64}{Population\ age\ 15-64}$)
$LifeExp_t$	Life Expectancy (Expected life expectancy at birth, instrumented by lagged life expectancy of 1,3 and 5 years

Table 1: Model Variables

Young Age Dependency Ratio (YADR) and Old Age Dependency Ratio (OADR) are commonly used indicators to shed light on the state of the age-group cohort of workers. In addition, it represents the composition of workers and their obligations to household care-giving such as taking time off work to attend to healthcare needs of elderly family members or caregiving duties to infants and young children.

Trade openness was included as a control in consideration of the export-led productivity hypothesis in attempt to disentangle the effects of trade-led productivity effects on labour productivity from that of life expectancy, given that Singapore has one of the highest trade openness in the world. Additional country specific characteristics were excluded given that the regression analysis is applied to only Singapore and not a panel of countries.

To address the issue of endogeneity I use lagged life expectancy as the instrumental variable for the endogenous variable of present life expectancy. Instruments must satisfy the assumptions of exogeneity and relevance. The relevance assumption is satisfied given that lagged life expectancy is highly correlated with present life expectancy. I argue that life expectancy in the past is not systematically correlated with current labour productivity, since present-day labour productivity is unlikely to be affected by life expectancy in the past, thus lagged life expectancy satisfies the exogeneity assumption.

However, this raises the question as to the extent of the time lag to employ the instrument. We face the trade-off where an increase in the extent of the time lag of the instrument is likely to better satisfy the exclusion restriction, but the longer time lag decreases the extent of correlation between the instrument and present life expectancy, and we further lose observation counts in our analysis. As such, for sensitivity analysis, we include regression results using 1,3 and 5-year lags of life expectancy as instruments.

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4. Results and Discussion

We provide some descriptive analysis of the life expectancy and productivity statistics used in our regression. Broadly, the scatterplot in Figure 2 suggests a positive correlation between life expectancy and labour productivity.

	Mean	Min	Max	Standard Deviation
Output per hour worked($)	74.8419	65.65983	83.49756	5.469317
Life Expectancy (years)	24.91061	3.900617	55.62515	15.42853
Trade Openness (% GDP)	328.8891	229.0534	437.3267	48.9365
Young-Age Dependency Ratio	39.17178	15.89687	87.54266	22.38267
Old-Age Dependency Ratio	7.886815	3.275036	16.1324	2.484249

Table 2: Summary Statistics of Data (59 observed periods 1961-2021)

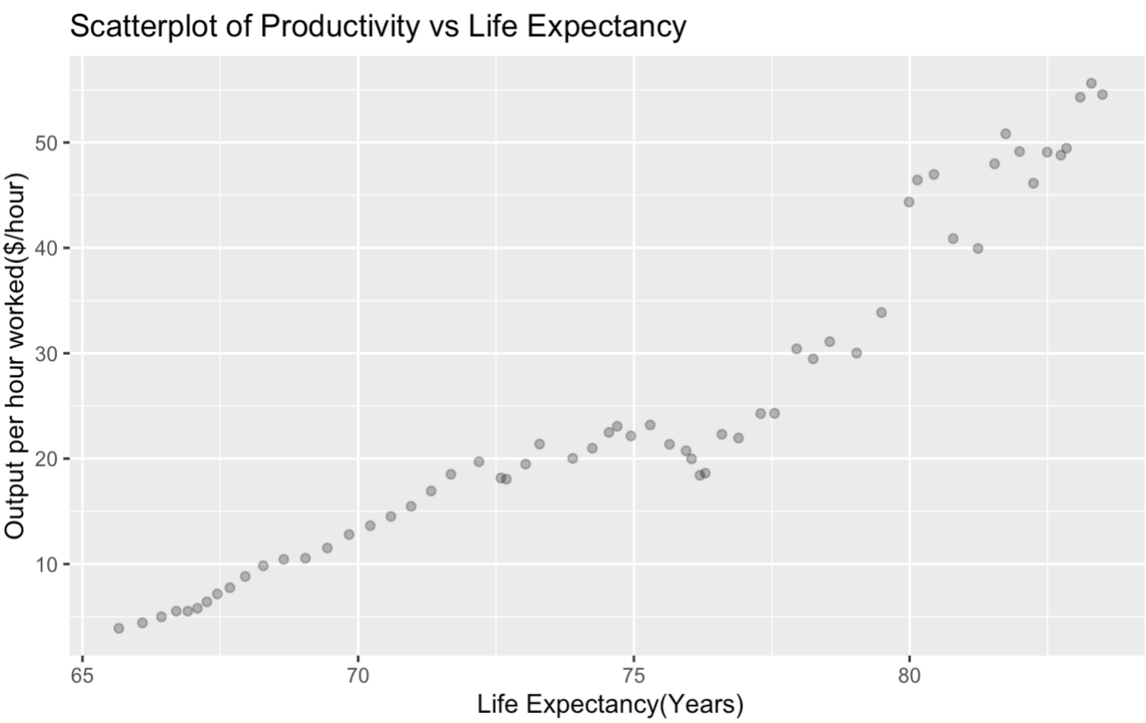

Figure 2: Scatterplot of Output per hour worked($/hour)(Penn World Table) vs expected Life Expectancy(Years)(World Development Indicators)

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This table summarises the regression results employing lagged log life expectancy of 1,3 and 5 years respectively as the instruments.

Dependent Variables	log(Output per hour worked) (1-year lagged life expectancy as the instrument)	log(Output per hour worked) (3-year lagged life expectancy as the instrument)	log(Output per hour worked) (5-year lagged life expectancy as the instrument)
log(Life Expectancy)	3.553847*** (0.778016)	3.748331*** (0.8345053)	4.326918*** (0.8706803)
Trade Openness	0.0017039*** (0.0004519)	0.0019365*** (0.0004563)	0.0020157*** (0.0004409)
Young Age Dependency Ratio	-0.0100618*** (0.0021616)	-0.0083206*** (0.0023329)	-0.0057029*** (0.0025694)
Old Age Dependency Ratio	0.0633977*** (0.0183787)	0.0641357*** (0.0182955)	0.0611554*** (0.0174422)

Table 3: Regression results
* Significant at 10%, ** Significant at 5%, *** Significant at 1%
(robust standard errors presented in parenthesis)

From these preliminary results, we can ascertain that when there is a more pronounced difference in willingness to pay for local amenities – as characterised by the presence of individuals with $\alpha = 1, 10,$ and 100 in the population – the Moran's I value reached after a number of periods falls, indicating a fall in income-segregation. This is like varying the income distribution but allows for more detailed interaction between agents' income and expenditure to be encoded using the MRS in future development.

Additionally, considering the potential for endogeneity bias stemming from the reverse causality of productivity on life expectancy, I performed relevant specification tests. First, I perform the endogeneity tests to ascertain if the endogenous regressors are, in fact, exogenous. The Hausman test rejects the claim that life expectancy is an exogenous variable and that 2SLS should be used instead of an OLS model. In addition, I perform the F-tests to assess the validity of the instruments. The Kleibergen-Paap F statistic suggests that the instruments are valid across the 1,3,5-year lagged life expectancy as the F-statistic across all three instruments at the first stage regression is much higher than the rule of thumb critical value of 10.

Table 3 shows that across the three instruments, the coefficient estimates remain largely comparable in terms of direction, magnitude, and statistical significance. The regression estimates suggest that life expectancy is positively associated with labour productivity and is statistically significant at 1% across the lagged life expectancy instruments. These results provide support in line with economic literature that life expectancy in Singapore is expected to raise labour productivity and are consistent with that of Cervellati and Sunde (2011) in finding that countries such as Singapore, which are characterised by declining fertility rates and life expectancy well above 50, will not experience the onset of Malthusian effects. Further analysis indicates the negative association between life expectancy and population growth rate across the time period used in the paper.

For brevity, discussing results from the IV regression with 3-year lagged life expectancy as the instrument, a 1 percentage point increase in life expectancy is expected to be associated with a 3.75 percentage points increase in output per hour worked on average. Comparing the magnitudes of coefficient estimates, we observe that the effect of life expectancy on labour productivity is much higher than that of both the YADR (-0.00832) and OADR(0.0641) and can broadly classify that life expectancy affects labour productivity more than the existing age structure composition of the economy.

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Additionally, as life expectancy in Singapore is expected to increase in the following decades, we can expect workforce ageing and a reduction in the labour supply growth. While this study suggests positive returns to increased life expectancy, with such low fertility rates in Singapore, we would expect an ageing workforce accompanied with a falling labour force participation rate, due to preferences for retirement and skills obsolescence among older workers. Furthermore, wages of the older workers need not necessarily reflect labour productivity similar across different age-cohorts as older workers may be paid more than their marginal productivity possibly due to deferred compensation structures that firms may adopt.

5. Conclusion

While much research has been done to determine the drivers of labour productivity growth in Singapore, such as wage supplement schemes, capital intensity strengthening, and productivity solutions grants, this paper provides the angle of population demographics and health outcomes in terms of life expectancy in furthering labour productivity in Singapore. As such, this paper raises the pertinence of the improvements in health outcomes and extending life expectancy in Singapore as a policy outcome of raising labour productivity. The improvement of health outcomes has typically been viewed as demographic risk management of ageing societies such as Singapore. However, this paper suggests that investments in health conditions to improve life expectancy should be consequentially considered as a key driver of labour productivity, and by extension economic growth in Singapore.

While this paper aggregates labour productivity in Singapore across the labour force, further research can be done to analyse the effects of labour productivity across sectors given that labour quality improvements are likely to affect sectors differently. Furthermore, different measures of labour productivity can be considered to better understand the interaction between the effects of population dynamics and life expectancy on labour productivity, both across the general population and of the labour force. Lastly, given that the reverse relationship and simultaneity are likely to hold true, where life expectancy is affected by labour productivity, it is worthwhile to examine the determinants of both life expectancy and labour productivity, such as healthcare systems and pension scheme structures.

Finally, given that productivity is comprised of many drivers beyond labour such as capital and state of technology in the economy, there is value in understanding the interactions between an ageing workforce on other productivity drivers. For instance, as the pool of older workers are likely to command higher wages increase, firms may be incentivised to uptake labour-saving capital such as industrial robots (Acemoglu and Restrepo, 2020), leading to differences in productivity gains between industries with greater propensity for automation relative to industries with fewer automation opportunities. Beyond raising the statutory retirement age as a mental anchor in influencing retirement decisions, to arrest the slowing labour supply growth, policies such as re-employment and job redesign can help older workers remain in employment and contribute to economic growth.

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Article

The Influence of Market Dynamics on Retail Investor Attention

James Symons-Hicks[1]

[1] Student (BSc Economics, 2020-23), Dept. of Economics, UCL, UK; james.symons-hicks.20@ucl.ac.uk

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Abstract

Retail investors have become increasingly active in global markets over the past several years. However, the factors that drive retail investors to focus on particular stocks are unclear. Using a sample of UK FTSE 100 stocks, this paper analyses whether stock volatility, liquidity, returns, and trading volume have the power to attract the attention of UK retail investors, measured using the Google Search Volume Index. Overall, this paper finds positive relationships between three of the dynamics (volatility, returns, and daily trading volume) and increased retail investor attention. Greater stock illiquidity also coincides with an increase in the Google Search Volume Index, although this may be due to liquidity-impacting events. When conditioning on stocks by quartiles of market capitalisation, I find that the effects of returns and trading volume are greater in magnitude for the top 25% of stocks.

Keywords: Retail Investors, Market Dynamics, Financial Markets, FTSE 100, Attention, Investor Behaviour.

1. Introduction

Retail investors have caught the attention of global media over the past several years, particularly for their potential to cause extreme market events. There are famous cases of asset prices soaring as a result of retail attention; GameStop, AMC, and Bitcoin are just a few of many examples. This paper seeks to identify which market dynamics capture the attention of retail investors. Attention is a scarce resource, which limits the amount of information that humans are able to process at any one time (Kahneman, 1973). Therefore, it is of interest to consider which market dynamics are sufficiently important to capture retail investors' attention; the dynamics considered in this paper are volatility, liquidity, returns, and daily trading volume.

Much of the literature focuses on the impact that retail investors have on markets: how they impact liquidity and volatility (Barrot et al., 2016; Foucault et al., 2011; Kelley and Tetlock, 2013), how their trading makes returns predictable (Barber et al., 2009), and how they impact price stability (Baig et al., 2022). However, few studies have investigated what attracts them to trading in the first place. Some studies which have looked at this topic include Hsieh et al. (2020) and Seasholes and Wu (2007); these study the impact of upper price limit events on investor attention, finding that such events generate an "attention-grabbing effect". Kaniel et al. (2008) find that volume shocks bring media attention to stocks, which, in turn, captures investors' attention.

Overall, there is a lack of literature that looks more generally, rather than event-specific studies, at the impacts of market dynamics on attention. Furthermore, the number of retail investors in the UK has increased over the past decade as a result of, amongst other factors, increased access to commission-free trading (Statista, 2021). This can be seen by the monthly number of active users on the major trading platforms (Figure 1).[1] As such, we need to consider the modern effects, given that the characteristics of these investors may change over time. There is very little UK-focused literature on this topic, and, since these investors can significantly impact markets, greater effort should be taken to understand their behaviour.

I use a sample of 87 stocks from the the UK's FTSE 100 index, and the Google Search Volume Index as a measure of retail investor attention. The empirical results suggest that changes in volatility, returns, and, to some extent, daily trading volume lead to increased retail investor attention. I find a positive relationship between illiquidity and attention, although this is likely due to exogenous, liquidity-impacting shocks that simultaneously capture investors' attention. When conditioning on stocks by quartiles of market capitalisation, I find that the effects of returns and trading volume are greater in magnitude for the top 25% of stocks. This suggests that for larger stocks, which are likely more widely publicised in the media, a shock to market dynamics has a greater impact on attention. For smaller stocks, even with larger shocks to dynamics, the resulting impact on attention is smaller.

The remainder of the paper is set out as follows: Section 2 analyses the current literature; Section 3 discusses the data sets used in the analysis; Section 4 explains the empirical methodology used; Section 5 presents the findings from the data; Section 6 discusses the implications of these findings; Section 7 concludes.

[1] Between January 2017 and May 2021 (the peak), we see a 395% increase in the number of active users each month. Excluding the COVID-19 pandemic, we still observe a 53% increase between January 2017 and February 2020.

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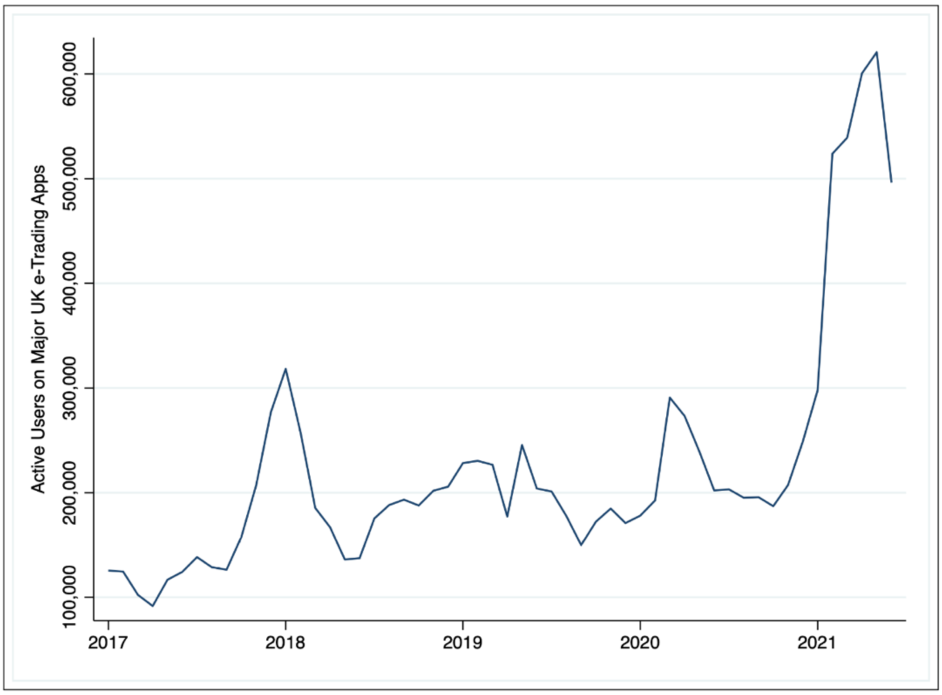

Figure 1: Number of Monthly Active Users on the Major e-Trading Apps (Statista, 2022)

2. Literature Review

A substantial volume of literature has analysed the impacts of retail investors on markets (e.g., Barber et al. (2022), Barber and Odean (2008), Cheng et al. (2021), and Da et al. (2011)); these papers commonly show that retail investors contribute to both market liquidity and volatility. However, very few papers look at this from the opposite direction, that is, considering the effects of preceding dynamics on attention.

Several papers have considered how retail investors' trades respond to attention-grabbing stocks, that is, those that "have experienced extreme returns, inflated trading volume, or been the subject of extensive headlines" (Gavish et al., 2021). Barber and Odean (2008) find that retail investors are net buyers of attention-grabbing stocks; Gavish et al. (2021) find that the magnitude of this effect depends on their level of sophistication. Barber and Odean use three measures to identify stocks that are likely to be attention-grabbing: news, unusual trading volume, and extreme returns. They use these measures as a proxy for whether investors were paying attention to a stock.

Seasholes and Wu (2007) study upper price limit events on the Shanghai Stock Exchange, finding that such events capture individual investors' attention because high returns and high trading volume generate news. Similarly, Hsieh et al. (2020) show that "reaching the price limit generates an attention-grabbing effect" for retail investors. Such events "induce individual investors to buy stocks they have not previously owned" (Seasholes and Wu, 2007). This is consistent with the findings of Kaniel et al. (2008): "it is reasonable to assume that individual investors do not follow all the stocks all the time but may be attracted to a certain stock after a volume shock brings media attention to it." Similarly, Engelberg and Parsons (2011) find that individual investors are more likely to trade a stock if it has appeared in the local newspaper. These results suggest that media attention is in response to market dynamics, thus acting as a 'stepping stone' between market dynamics and the resulting retail investor attention. The extent to which the media focuses on these dynamics is a factor that determines the strength of transmission between market dynamics and attention (Engelberg and Parsons, 2011).[2] This mechanism will not, however, be the primary focus of this paper.

Welch (2022) finds that retail investors are collectively attracted to volatility and to "stocks with high past share volume and dollar-trading volume". Welch hypothesises that they may enjoy the risk associated with holding these stocks. During return- and turnover-based attention-grabbing events, "an increase in retail trading...is associated with an increase in idiosyncratic volatility"

[2] Engelberg and Parsons (2011) find that, when reacting to "the same set of information events (earnings releases of S&P 500 Index firms), the presence or absence of local media coverage is strongly related to the probability and magnitude of local trading".

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(Brandt et al., 2010). Similar to this paper, but without a focus on equities, Urquhart (2018) uses the Google Search Volume Index (SVI) to analyse the effects of shocks on volatility, volume, and returns on Bitcoin attention, finding that volatility and volume significantly impact attention the following day.

A factor not relating directly to market dynamics but still potentially impacting attention is local peer performance.[3] Kaustia and Knüpfer (2012) find a positive effect of local peer performance on participation the following month, but only for positive returns. This supports the idea that individuals extrapolate from peer outcomes and that stories of high returns encourage other investors. Kaustia and Knüpfer suggest that these results "are likely to be stronger in populations with more wide-spread stock market participation", making the UK a good market to consider given the low cost for retail investors to access markets.[4]

Recent literature has identified the Google SVI as an accurate indicator of retail investor attention (Da et al., 2011; Ding and Hou, 2015; Smales, 2021). Whilst many studies analyse the impact of attention-grabbing events on retail investors, they use noisy proxies for what constitutes an attention-grabbing event; Google SVI is a cleaner proxy and a trusted measure for attention. Whereas institutional investors use services such as Bloomberg, the vast majority of retail investors instead use the internet, namely Google, as their source of information. Da et al. (2011) argue that the Google SVI is a direct and accurate measure of retail investor attention for several reasons. Firstly, Google remains the most popular search engine; moreover, "search is a revealed attention measure": if someone is searching for something, they are paying attention to it.

3. Data

The data used in this analysis is split into two categories: UK financial market data and investor attention data.

3.1 Refinitiv FTSE 100 Data

The FTSE 100 pricing data was obtained from the Refinitiv Data platform, and ranges between 01 January 2017 and 01 July 2022. The information contains opening and closing prices, daily high and low values, daily market capitalisation of each stock, daily trading volume, daily turnover (total trade value for a given market day), and closing bid and ask prices. This data is used to create the measures of liquidity, volatility, and daily returns, which are, in turn, used to form the analysis.

There are five stocks for which the data is truncated due to different listing dates on the London Stock Exchange.

The ticker symbols for these stocks are: *AAF, AVST, EDV, MNG*, and *PSH*. These have been removed from the analysis. For a full list of the stocks in the data set, see Table A1 in the Appendix.

Table 1 shows the summary statistics for the data retrieved from the Refinitiv Data platform. Table 2 shows the summary statistics for the spreads and returns generated using this data.

[3] Peers are here defined as individuals to which the person of interest is connected, whether this be friends, family, co-workers, or as is common for many online traders, social media connections.
[4] Many platforms have and continue to emerge in the UK over the last decade that offer commission-free trading to retail investors. Previously, high, fixed transaction costs per trade meant that trading was only economically viable for those retail investors who were willing and able to trade larger amounts. This is no longer the case; for example, Trading212 offers trading from as little at £1.

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Table 1: Summary Statistics for FTSE 100 Constituents

	Mean	**Std. Dev.**	**Min.**	**Max.**
Open Price	50.94	298.64	0.24	4267.65
Close Price	52.94	298.54	0.24	4263.64
High Price	53.61	302.70	0.25	4299.74
Low Price	52.27	294.44	0.24	4195.46
Closing Bid	52.93	298.44	0.24	4259.63
Closing Ask	52.96	298.66	0.24	4263.64
Daily Volume	8.98M	25.70M	11288	1.41B
Market Cap.	21.60B	29.90B	104.00M	233.00B
Turnover	68.10M	257.0M	63882.70	27.70B

All values rounded to two decimal places.
Observations: 120, 835
Note: M refers to million - i.e., 1M = 1×10^6. B refers to billion - i.e., 1B = 1×10^9.

Table 2: Summary Statistics for FTSE 100 Returns & Spreads

	Mean	**Std. Dev.**	**Min.**	**Max.**
Returns				
1-Day Return	0.0003	0.0206	-0.5747	0.5668
5-Day Return	0.0013	0.0461	-0.8134	0.9648
Spreads				
Absolute Spread	0.0373	0.3106	0.00*	24.0657
Relative Spread	0.0006	0.0001	0.00*	0.2026

All values rounded to four decimal places.
*There are only three instances for which the closing spread is 0. When excluding these, the minimum absolute and relative spreads are 0.00005 and 0.0001, respectively. The mean, standard deviation, and maximum values remain unchanged to four decimal places.

3.2 Google Search Volume Index

As a measure of retail investor attention, I use the Google SVI for the ticker symbol, following Da et al. (2011).[5] The data provides a weekly index for searches of a given term, with values ranging between 0 and 100. Da et al. choose to use the ticker symbol rather than the company name as it is "less ambiguous", stating that if an investor is searching for a particular stock symbol, they are likely doing so because they are interested in the financial information of the company.

In some cases, the search term was combined with the word 'share' to avoid ambiguity with other similar searches; this judgement was made based on the 'related topics' component from Google Trends.[6] To ensure robustness, I conduct dummy variable regressions to test for statistical significance of the effects of noisy searches. These results are reported in Appendix B.1. Overall, I find that the results are not affected significantly when using only the subset of 'clean' ticker symbols.

5 This data is obtained from Google Trends, which is available at https://trends.google.co.uk/.
6 For a further explanation, I refer to Appendix A.2.

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There are eight stocks for which the Google Trends data is excluded. This is due to the fact that the ticker symbol only is too ambiguous, but there is missing data when using the ticker symbol appended with 'share'. These stocks are: DPH, FLTR, HIK, ICP, LAND, RS1, SDR, and SKG. Thus, when combining the financial pricing data (five stocks removed) and Google SVI data (eight stocks removed), the analysis is conducted with 87 stocks. Although the exclusion of these stocks is not ideal, this is unlikely to significantly affect the empirical results, given that the models are run at the stock-level and the SVI data is an index, not an absolute value, meaning that the analysis considers *changes* in this index.

One potential issue caused by the missing data is for the quantile regression models (discussed in Section 4.4); several of these eight stocks have a lower than average market capitalisation, implying that some of the models conditioning on the bottom 25% of stocks by market capitalisation may be biased to some extent. This is not overly problematic, however, as the number of excluded stocks due to missing data is low.

4. Methodology

This section will discuss the empirical methods used in the analysis. The results are reported in Section 5 and are discussed in Section 6.

4.1 Measures of Explanatory Variables

Firstly, I define the empirical proxies used for the measures of liquidity and volatility. In the descriptions below, X_d and X_t refer to observations of variable X at the daily and weekly levels, respectively.

4.1.1 Volatility Measures

Financial volatility refers to the fluctuations in the returns of an asset, most commonly, to the standard deviation, $\hat{\sigma}$, or variance, $\hat{\sigma}^2$, over a set of observations (Poon and Granger, 2003). The variance is given by:

$$\hat{\sigma}_{i,t}^2 = \frac{1}{N-1}\sum_{t=1}^{N}(R_{i,d} - \bar{R}_i)^2, \tag{1}$$

where $R_{i,d}$ is the return of stock i on a given day d and $\bar{R}_i$ is the sample mean of stock i. N is the number of observations in a given week. I use the standard deviation measure, $\hat{\sigma}_{i,t}$, in my analysis; in the regressions below, this measure, at the weekly level, will be denoted by $Volatility_t$.

I also use a range-based volatility measure, $LogRange$, following Alizadeh et al. (2002), in which the volatility is given as the difference in the intraday log high and low quoted prices:

$$LogRange_{i,d} = ln(high_{i,d}) - ln(low_{i,d}). \tag{2}$$

The daily value of $LogRange_{i,d}$ is then averaged at the weekly level.

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4.1.2 Liquidity Measures

In my analysis, I use two measures of liquidity (or, conversely, illiquidity): the quoted closing bid-ask spread and Amihud (2002)'s illiquidity measure. Firstly, the quoted bid-ask spread is a simple measure of liquidity; a narrower spread refers to greater liquidity and lower trading costs. In absolute terms, the bid-ask spread is:

$$S_{i,d} = a_{i,d} - b_{i,d},$$

where $a_{i,d}$ and $b_{i,d}$ are the daily closing ask and bid quotes, respectively. However, we can look at this in relative terms by dividing this by the midpoint of the two prices:

$$s_{i,d} \equiv \frac{S_{i,d}}{m_{i,d}} = \frac{a_{i,d} - b_{i,d}}{m_{i,d}}, \tag{3}$$

where $m_{i,d} = \frac{a_{i,d}+b_{i,d}}{2}$. In the models presented in Section 4.2, I will denote the relative spread by $Spread_{i,t}$.

Unfortunately, given the limited access to microstructure (intra-day) data on bid-ask spreads, this analysis is limited to closing bid-ask spreads. This may be a limitation to some of the quantitative results presented. The second measure of liquidity used in my analysis, Amihud (2002)'s illiquidity ratio, is given by:

$$Illiq_{i,d} = \frac{|R_{i,d}|}{Volume_{i,d}}, \tag{4}$$

where $|R_{i,d}|$ is the absolute daily return of stock i and $Volume_{i,d}$ is the daily monetary trading volume of the corresponding stock. The weekly average is denoted by $Illiq_{i,t}$. In my analysis, I use the logarithmic transformation, log $(Illiq)_{i,t}$, to make the interpretation of the regression coefficients more intuitive.

4.2 Regression Models

This section will present the panel autoregressive models used in the analysis. The autoregressive distributed lag (ADL) models employed in the analysis account for the potentially persistent nature of the variables of interest, as well as the attention index in prior weeks. In the analysis, I consider both models that separate the variables of interest, as well as those that combine the various specifications; these can be seen in Section 4.3.

Table 3: Recommended Lags of Each Variable by Information Criterion

Variable	AIC	BIC	Figure
Attention	2	2	*Figure 2*
Volatility	3	2	*Figure 3*
LogRange	1	1	
Spread	3	2	*Figure 4*
log(*Illiq*)	4	4	
1*DRet*	0	0	*Figure 5*
5*DRet*	4	1	
log(*Volume*)	3	1	*Figure 6*

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I consider both the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC); when there are differences between the two criteria, I favour the AIC. This is because the AIC has lower penalties than the BIC for additional lags, favouring 9 larger models than the BIC; this allows for the analysis of dynamics of the lags in this paper. The criteria are given by choose p so as to minimise the following expressions (Stock and Watson, 2020):

$$AIC(p) = \log\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{2}{T}, \tag{5}$$

$$BIC(p) = \log\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{log(T)}{T}, \tag{6}$$

where p is the number of lags and T is the number of time periods. The first term is decreasing in p, whilst the second is increasing; hence, the second term is the penalty for higher lags.[7] The recommended lags for each of the variables according to the criteria can be seen in Table 3.

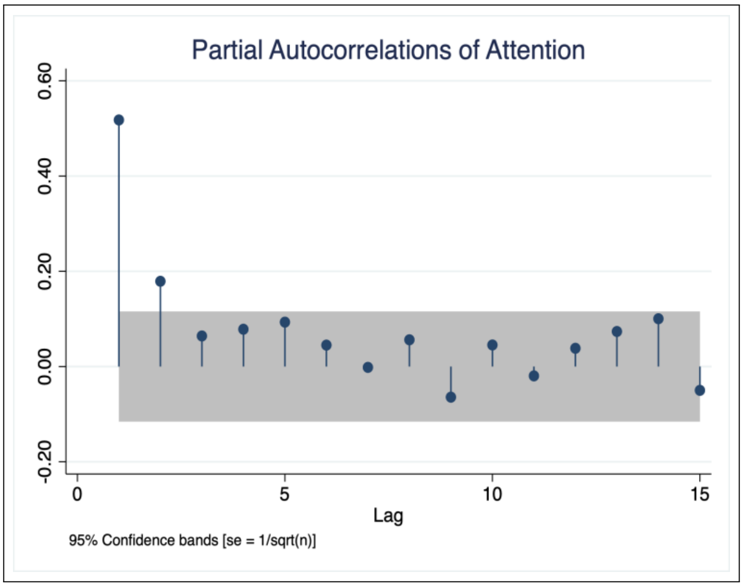

Figure 2: Partial Autocorrelation Function for the Google SVI

Figure 2 shows persistent nature of the Google SVI data, $Attention_t$, through the partial autocorrelation (PAC) function. According to this, after two weeks, the lags of the index produce no additional impact on the current week.

4.2.1 Volatility Models

The volatility models use three lags for $Volatility_t$ and two for $LogRange$. Whilst the AIC recommends one lag for $LogRange$, I increase this to two lags as previous lags may be of interest due to the potential for delayed reactions to the market dynamics, or due to reversals. The PAC functions for the volatility measures can be seen in Figure 3.

[7] The first term is decreasing, or at least non-increasing, in p as SSR(p) is decreasing, or at least nonincreasing, in p.

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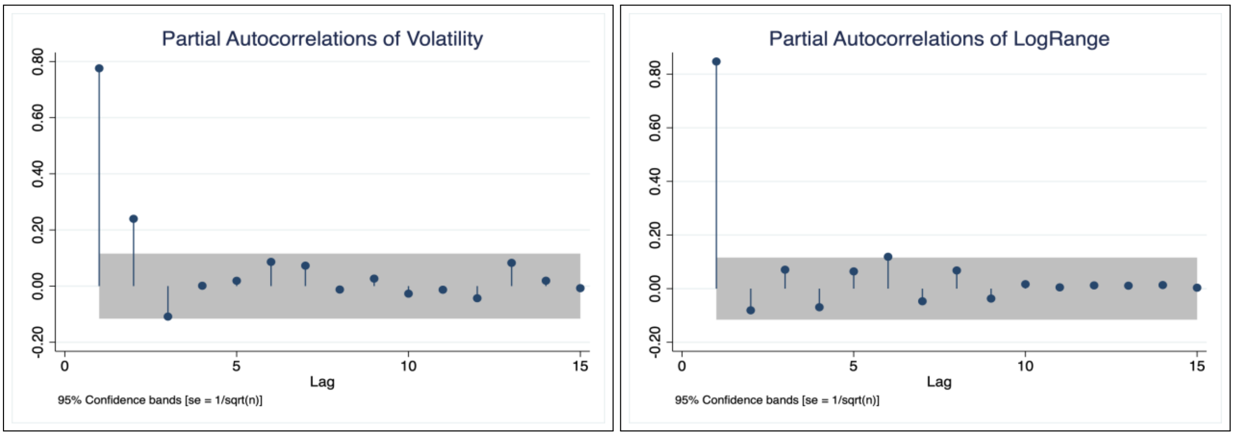

Figure 3: Partial Autocorrelation Functions for *Volatility* and *LogRange*.

Θ_i is a vector of stock-specific characteristics, following Baig et al. (2022).[8] These controls, averaged at the weekly level, are the log of daily turnover ($\log(Turnover)_t$), closing bid-ask spreads ($ClosingSpread_t$), and log of the stock's market capitalisation($\log\ (MarketCap)_t$).

Regression Model 1

$$Attention_{i,t} = \alpha + \beta_0 Volatility_{i,t} + \sum_{j=1}^{3} \beta_j Volatility_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Theta_i$$

Regression Model 2

$$Attention_{i,t} = \alpha + \beta_0 LogRange_{i,t} + \sum_{j=1}^{2} \beta_j LogRange_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Theta_i$$

4.2.2 Liquidity Models

Three and four weeks of lags are implemented for $Spread$ and $\log\ (Illiq)$, respectively. The PACs for the measures are in Figure 3. In the liquidity models, Φ_i is a reduced vector of controls that includes only $\log\ (MarketCap)_t$ and $\log\ (Turnover)_t$ due to collinearity when including the absolute spread and relative spread.

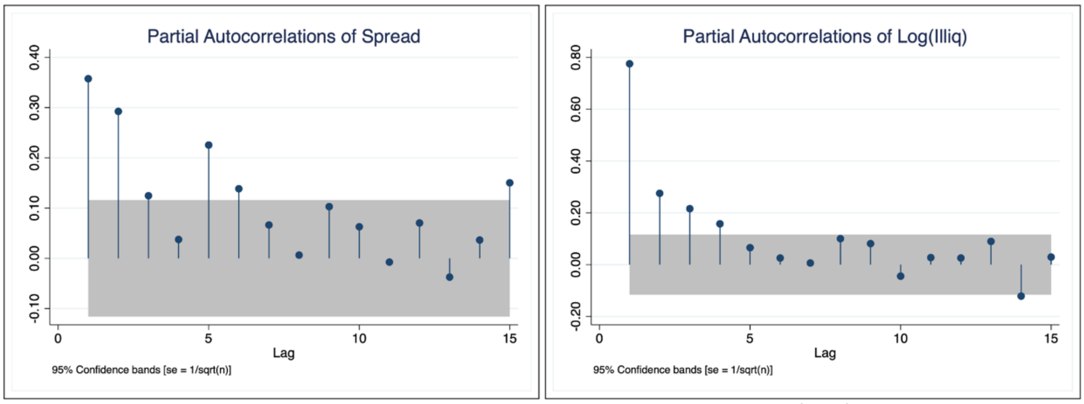

Figure 4: Partial Autocorrelation Functions for $Spread$ and $\log(Illiq)$.

[8] Although Baig et al. focus on the impact of retail investors on market volatility, the opposite direction of interest to this paper, it is likely that these variables still serve as relevant controls in the models discussed.

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Regression Model 3

$$Attention_{i,t} = \alpha + \beta_0 Spread_{i,t} + \sum_{j=1}^{3} \beta_j Spread_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Phi_i$$

Regression Model 4

$$Attention_{i,t} = \alpha + \beta_0 \log(Illiq)_{i,t} + \sum_{j=1}^{4} \beta_j \log(Illiq)_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Phi_i$$

Returns Models

In the models below, I use both 1-day ($1DRet_{i,t}$) and 5-day ($5DRet_{i,t}$) returns to analyse how attention responds to changes in the price of a given stock. Both variables are averaged at the weekly level, but the 5-day return allows for the testing of whether returns need to immediate or gradual for them to capture retail attention. $5DRet_{i,t}$ is a 5-day rolling return that is then averaged at the weekly level.

For 1-day returns, the recommendation by the AIC and BIC is to use only the current week, implying no persistence in the time series. However, as mentioned above, it is worth considering the potential for delayed reactions to the change in dynamics; thus, I include two lags of $1DRet$ as a measure. For the 5-day returns, I include four lags. The PACs can be seen in Figure 5.

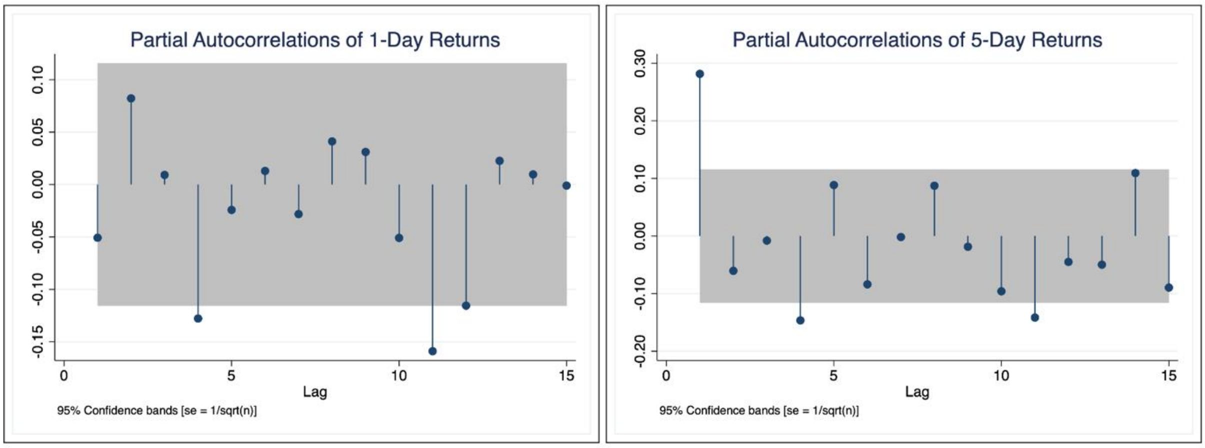

Figure 5: Partial Autocorrelation Functions for $1DRet$ and $5DRet$.

Regression Model 5

$$Attention_{i,t} = \alpha + \beta_0 \cdot 1DRet_{i,t} + \sum_{j=1}^{2} \beta_j \cdot 1DRet_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Theta_i$$

Regression Model 6

$$Attention_{i,t} = \alpha + \beta_0 \cdot 5DRet_{i,t} + \sum_{j=1}^{4} \beta_j \cdot 5DRet_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Theta_i$$

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Trading Volume Model

In the model below, $Volume_{i,t}$ refers to the average daily shares of stock *i* traded in a given week. I use log(*Volume*) to make the interpretation more intuitive. The PAC for log(*Volume*) is shown in Figure 6.

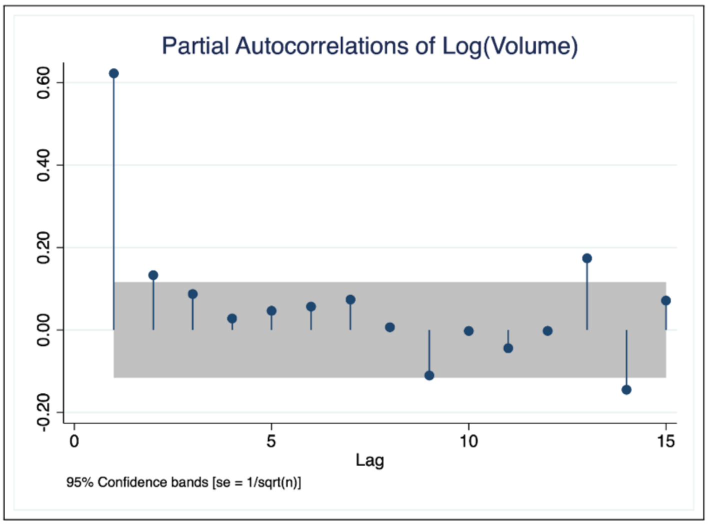

Figure 6: Partial Autocorrelation Function for $\log(Volume)$.

Regression Model 7

$$Attention_{i,t} = \alpha + \beta_0 \cdot \log(Volume)_{i,t} + \sum_{j=1}^{3} \beta_j \log(Volume)_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Theta_i$$

4.3 Combined Regression Specifications

This section combines several of the regression specifications above into a single model to test the effects when considering multiple dynamics. Due to collinearity between the measures, each model will contain only one measure of each variable of interest, except for returns given the differing dynamics of 1-day and 5-day returns. As there are two measures for both volatility and liquidity, the analysis uses four combined models that consider the combinations of these measures. That is, the four will contain the following combination of measures:

*{Volatility,Spread},{Volatility,*log(*Illiq*)*},{LogRange,Spread},{LogRange,*log(*Illiq*)*}*.

An example for the first specification can be seen in Model 8 below.

Regression Model 8

$$\begin{aligned} Attention_{i,t} \quad = \quad & a + \sum_{j=0}^{3} \beta_{1,j} \cdot Volatility_{i,t-j} + \sum_{j=0}^{3} \beta_{2,j} \cdot Spread_{i,t-j} \\ & + \sum_{j=0}^{2} \beta_{3,j} \cdot 1DRet_{i,t-j} + \sum_{j=0}^{4} \beta_{4,j} \cdot 5DRet_{i,t-j} \\ & + \sum_{j=0}^{3} \beta_{5,j} \cdot \log(Volume)_{i,t-j} + \sum_{k=1}^{2} \gamma_k Attention_{i,t-k} + \delta \cdot \Phi_i \end{aligned}$$

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4.4 Regressions by Market Capitalisation

It is also of interest to consider how the impacts on attention vary across levels of market capitalisation. I classify a given stock by using the average market capitalisation of that stock over the entire sample; these are split into the bottom 25%, middle 50% (interquartile range), and the top 25% of stocks by market capitalisation. The quartile values for the sample are given in Table 4.

Table 4: Average Market Capitalisation Quartiles

25%	Median	75%
6.10B	8.64B	21.30B

Observations: 87. B refers to billion - i.e., 1B = 1×10^9.
Note: These values use the average of each stock over the entire sample period.

I run the models above conditioning on subsets of the data set, split into the three groups. I then test for statistically significant differences across the regression coefficients using:

$$Z = \frac{\hat{\beta} - \tilde{\beta}}{\sqrt{\hat{se}^2 + \tilde{se}^2}}, \tag{7}$$

under the assumption that $Z \sim N(0, 1)$ in large samples. $\hat{\beta}$ and $\widehat{se}$ refer to the regression coefficient and corresponding standard error of one subset of the data and $\hat{\beta}$ and $\widetilde{se}$ refer to the regression of the coefficient and corresponding standard error of another subset.

5. Results

This section presents the empirical results from the models in Section 4.2. Each of these models are split into three columns in the output below: (i) gives the most basic model, with just the variable of interest and controls; (ii) gives the full model using heteroskedasticity- and autocorrelation-consistent (HAC) standard errors but without accounting for panel fixed effects; (iii) is the full model that accounts for fixed effects and uses HAC standard errors.

The models below use the Newey-West estimator for the HAC standard error, with the truncation parameter, *m*, as given by Stock and Watson (2020):

$$m = 0.75 \times T^{\frac{1}{3}},$$

where T is the number of time periods within the sample. The parameter, *m*, is rounded up to the nearest integer. The data set used contains $T = 287$ weeks of data; thus, I set $m = 5$.

Tables 5 and 6 present the output from the volatility regression models for *Volatility* and *LogRange*, respectively. Focusing on column (iii), we see that the coefficients are significant at the 1% level for both volatility measures at week t.

For *Volatility*, only $Volatility_t$ and $Volatility_{t-2}$ show statistical significance, whilst lags one and three are insignificant. The coefficient on $LogRange_t$ is positive and significant at the 1% level, but $LogRange_{t-1}$ is negative at the 5% level. A one standard deviation increase in *Volatility*, equal to 1.41 pence (£0.0141), correlates with a 1.8 unit increase in the attention index. For *LogRange*, a 1% increase in the range between the daily high and low values coincides with a 1.16% increase in the index. Given that the mean value of the Google SVI is 30.93, this corresponds to a 0.36 unit increase.

Tables 7 and 8 present the output from the liquidity regression models for *Spread* and log(*Illiq*), respectively. Overall, the results are mainly statistically insignificant for the spread models, with some significance when using log(*Illiq*). For relative spreads, column (iii) shows that the coefficient on $Spread_{t-2}$ is statistically significant at the 10% level (p-value = 0.093), however, the remainder of the coefficients for *Spread* are statistically insignificant. Table 8, show that $\log(Illiq)_t$ is significant at the 1% level, along with

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some of the lags of this measure at varying levels of significance. The results suggest that a 1% increase in the illiquidity ratio coincides with a 1.03 point increase in the attention index in that week. The implications of these findings are discussed in Section 6.

Table 5: *Volatility* Regression Models

	$Attention_t$		
Model 1	(i)	(ii)	(iii)
$Volatility_t$	131.2128***	186.7333***	130.2388***
	(10.0294)	(13.44)	(12.7593)
$Volatility_{t-1}$		7.3881	9.1998
		(10.8825)	(10.396)
$Volatility_{t-2}$		-67.5204***	-39.4893***
		(12.0943)	(10.8827)
$Volatility_{t-3}$		-5.2394	-0.1816
		(10.2674)	(10.2214)
$Attention_{t-1}$		0.3651***	0.2150***
		(0.0066)	(0.0075)
$Attention_{t-2}$		0.3289***	0.1801***
		(0.0069)	(0.0077)
$\log(Turnover)_t$	5.0519***	0.7449***	3.9762***
	(0.3188)	(0.1955)	(0.2102)
$ClosingSpread_t$	1.2759	-2.7068***	1.6476**
	(1.0336)	(0.6707)	(0.6575)
$\log(Marketcap)_t$	-3.9664***	0.7893***	-2.8887***
	(0.4624)	(0.1849)	(0.2038)
Constant	33.6098***	-23.8176***	15.4382***
	(10.0166)	(2.7796)	(3.2358)
Fixed Effects	-	-	Yes
HAC Standard Errors	-	Yes	Yes
N	24,969	24,708	24,708

Note: $\log(Turnover)$, $ClosingSpread$, and $\log(MarketCap)$ are weekly averages by stock.
( ) = standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

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Table 6: *LogRange* Regression Models

	$Attention_t$		
Model 2	(i)	(ii)	(iii)
$LogRange_t$	107.2477***	186.0002***	115.6583***
	(10.0294)	(23.4716)	(19.6155)
$LogRange_{t-1}$		-43.6401***	-28.7237**
		(14.4246)	(13.117)
$LogRange_{t-2}$		-44.5276***	-16.3331
		(14.9338)	(12.8642)
$Attention_{t-1}$		0.3666***	0.2159***
		(0.0065)	(0.0075)
$Attention_{t-2}$		0.3269***	0.1779***
		(0.0069)	(0.0077)
$\log(Turnover)_t$	5.3436***	0.9004***	4.3165***
	(0.3186)	(0.2032)	(0.2203)
$ClosingSpread_t$	1.1882	-2.9907***	1.5945**
	(1.0351)	(0.6764)	(0.6583)
$\log(Marketcap)_t$	-4.0494***	0.7395***	-3.1460***
	(0.4707)	(0.1917)	(0.2114)
Constant	30.3459***	-25.4194***	15.7448***
	(10.1405)	(2.8528)	(3.2881)
Fixed Effects	-	-	Yes
HAC Standard Errors	-	Yes	Yes
N	24,969	24,795	24,795

Note: $\log(Turnover)$, $ClosingSpread$, and $\log(MarketCap)$ are weekly averages by stock.
( ) = standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

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Table 7: $Spread$ Regression Models

	$Attention_t$		
Model 3	(i)	(ii)	(iii)
$Spread_t$	-569.3428**	170.5256	-291.5251
	(258.9486)	(207.4634)	(238.1030)
$Spread_{t-1}$		139.0290	-308.0519
		(201.3943)	(206.6847)
$Spread_{t-2}$		189.3880	-329.7626*
		(212.6291)	(196.4395)
$Spread_{t-3}$		529.0155**	16.0428
		(229.5922)	(261.7005)
$Attention_{t-1}$		0.3708***	0.2148***
		(0.0065)	(0.0075)
$Attention_{t-2}$		0.3298***	0.1779***
		(0.0068)	(0.0076)
$\log(Turnover)_t$	6.5969***	0.9053***	5.4481***
	(0.2983)	(0.1666)	(0.1948)
$\log(MarketCap)_t$	-5.9796***	0.6745***	-4.7588***
	(0.4504)	(0.1712)	(0.2137)
Constant	56.5495***	-22.5957***	36.0385***
	(10.1526)	(3.019)	(3.823)
Fixed Effects	-	-	Yes
HAC Standard Errors	-	Yes	Yes
N	24,969	24,708	24,708

Note: $\log(Turnover)$ and $\log(MarketCap)$ are weekly averages by stock. ( ) = standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

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Table 8: *Illiq* Regression Models

	$Attention_t$		
Model 4	(i)	(ii)	(iii)
$\log(Illiq)_t$	1.9668***	1.2668***	1.0306***
	(0.2103)	(0.2346)	(0.2217)
$\log(Illiq)_{t-1}$		0.6092***	0.2115
		(0.2369)	(0.2196)
$\log(Illiq)_{t-2}$		0.7538***	0.4338*
		(0.244)	(0.2233)
$\log(Illiq)_{t-3}$		0.8838***	0.6483***
		(0.2352)	(0.2194)
$\log(Illiq)_{t-4}$		0.6963***	0.5353**
		(0.2241)	(0.2097)
$Attention_{t-1}$		0.3637***	0.2135***
		(0.0065)	(0.0074)
$Attention_{t-2}$		0.3257***	0.1775***
		(0.0068)	(0.0076)
$\log(Turnover)_t$	7.7065***	4.4560***	6.7731***
	(0.3215)	(0.2638)	(0.2857)
$\log(MarketCap)_t$	-4.8174***	1.2887***	-3.0056***
	(0.4505)	(0.1510)	(0.1896)
Constant	53.4931***	-4.2015	35.0750***
	(9.8888)	(2.7090)	(3.355)
Fixed Effects	-	-	Yes
HAC Standard Errors	-	Yes	Yes
N	24,969	24,621	24,621

Note: $\log(Turnover)$ and $\log(MarketCap)$ are weekly averages by stock.
( ) = standard errors.
*: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$.

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Tables 9 and 10 present the 1-day and 5-day return models, respectively. For 1*DRet*, only the current week, $1DRet_t$, is statistically significant at the 1% level, with the first and second lags having *p*-values of 0.095 and 0.069, respectively. The coefficient on $1DRet_t$ suggests that a 10% increase in the daily return is associated with a 5.4 point increase in the attention index. For 5*DRet*, a 10% increase in the returns over a 5-day period correlates with an increase in the Google SVI of 1.76 points. I find that, when using a one-sided hypothesis test, the coefficient on $1DRet_t$ is statistically greater than the coefficient for $5DRet_t$ (*p*-value = 0.005).[9] The results suggest that a one standard deviation increase in $1DRet_t$ coincides with a 1.11 unit increase in the SVI, whereas a one standard deviation increase in $5DRet_t$ coincides with a 0.81 unit increase, despite 5*DRet* having a standard deviation that is twice as large as that for 1*DRet*.[10]

Table 11 presents the empirical results from the trading volume regressions. Column (iii) shows that $\log(Volume)_t$ and $\log(Volume)_{t-2}$ are both statistically significant at the 1% level, whereas $\log(Volume)_{t-1}$ and $\log(Volume)_{t-3}$ are statistically insignificant. The coefficient on $\log(Volume)_t$ in column (iii) suggests that a 10% increase in the trading volume correlates with a 0.79% increase in the attention index; using the mean value of the SVI, this corresponds to a 0.24 point increase. The coefficient on $\log(Volume_{t-2})$ is also statistically significant at the 1% level. This coefficient suggests that a 10% increase in trading volume two weeks prior is associated with a decrease in the attention index of 0.15 points. This will be discussed in Section 6.

Table 9: 1*DRet* Regression Models

	$Attention_t$		
Model 5	(i)	(ii)	(iii)
$1DRet_t$	67.7632***	33.2121**	54.037***
	(12.9101)	(14.5796)	(13.6429)
$1DRet_{t-1}$		-7.8089	20.8679*
		(13.0000)	(12.5103)
$1DRet_{t-2}$		-9.9311	21.6406*
		(12.3462)	(11.9163)
$Attention_{t-1}$		0.3702***	0.2151***
		(0.0065)	(0.0074)
$Attention_{t-2}$		0.3282***	0.1764***
		(0.0068)	(0.0076)
$\log(Turnover)_t$	6.6259***	1.6152***	5.4945***
	(0.2980)	(0.2229)	(0.2313)
$ClosingSpread_t$	1.5431	-4.1144***	1.8796***
	(1.0363)	(0.7410)	(0.6716)
$\log(MarketCap)_t$	-5.8404***	-0.0800	-4.6252***
	(0.4417)	(0.1934)	(0.2190)
Constant	52.4018***	-16.4502***	31.5435***
	(9.9391)	(2.6322)	(3.2985)
Fixed Effects	-	-	Yes
HAC Standard Errors	-	Yes	Yes
N	24,969	24,795	24,795

Note: $\log(Turnover)$, $ClosingSpread$, and $\log(MarketCap)$ are weekly averages by stock.
( ) = standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

[9] This hypothesis was tested using the formula for the critical values given in Equation (7).

[10] The standard deviations for $1DRet_t$ and $5DRet_t$ are 0.0206 and 0.0461, respectively (Table 2).

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Table 10: $5DRet$ Regression Models

	$Attention_t$		
Model 6	(i)	(ii)	(iii)
$5DRet_t$	20.1509***	11.7312***	17.5698***
	(3.2646)	(3.9274)	(3.6867)
$5DRet_{t-1}$		-6.1761*	-0.3866
		(3.3258)	(3.0896)
$5DRet_{t-2}$		0.0744	6.4317**
		(3.2074)	(3.1214)
$5DRet_{t-3}$		-1.1756	1.8341
		(3.3134)	(3.1726)
$5DRet_{t-4}$		-2.4439	2.5111
		(3.0756)	(3.0644)
$Attention_{t-1}$		0.3717***	0.2166***
		(0.0066)	(0.0075)
$Attention_{t-2}$		0.3281***	0.1769***
		(0.0068)	(0.0077)
$Log(Turnover)_t$	6.6722***	1.6226***	5.5806***
	(0.2992)	(0.2242)	(0.2336)
$ClosingSpread_t$	1.4897	-4.1214***	1.9116***
	(1.0369)	(0.7426)	(0.6696)
$Log(MarketCap)_t$	-5.9373***	-0.1064	-4.7911***
	(0.4435)	(0.1942)	(0.2221)
Constant	53.8583***	-16.0200***	33.8236***
	(9.9764)	(2.6274)	(3.3236)
Fixed Effects	-	-	Yes
HAC Standard Errors	-	Yes	Yes
N	24,882	24,534	24,534

Note: $\log(Turnover)$, $ClosingSpread$, and $\log(MarketCap)$ are weekly averages by stock.
( ) = standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

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Table 11: log($Volume$) Regression Models

	$Attention_t$		
Model 7	(i)	(ii)	(iii)
$\log(Volume)_t$	9.1303***	6.8632***	7.918***
	(0.5112)	(0.4420)	(0.4233)
$\log(Volume)_{t-1}$		-1.0823**	0.4377
		(0.4595)	(0.4243)
$\log(Volume)_{t-2}$		-3.2797***	-1.5254***
		(0.4690)	(0.4317)
$\log(Volume)_{t-3}$		-1.1997***	-0.1730
		(0.3908)	(0.3678)
$Attention_{t-1}$		0.3608***	0.2099***
		(0.0066)	(0.0075)
$Attention_{t-2}$		0.3278***	0.1772***
		(0.0070)	(0.0078)
$\log(Turnover)_t$	-0.8507*	-0.2313	-0.7473***
	(0.5103)	(0.1836)	(0.213)
$ClosingSpread_t$	1.9265*	0.0562	1.7604**
	(1.0307)	(0.6275)	(0.7098)
$\log(MarketCap)_t$	-0.6034	0.5620***	-0.0668
	(0.5276)	(0.1659)	(0.1909)
Constant	-75.778***	-18.7270***	-65.3375***
	(12.2371)	(2.7067)	(3.2005)
Fixed Effects	-	-	Yes
HAC Standard Errors	-	Yes	Yes
N	24,969	24,708	24,708

Note: $\log(Turnover)$, $ClosingSpread$, and $\log(MarketCap)$ are weekly averages by stock.
( ) = standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

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5.1 Results for Combined Models

This section presents the results from the four combined models in Section 4.3. In the interest of space, Table 12 shows the coefficient of each variable for the current week only, however, the regressions are calculated using the full set of lags. For the extended regression table, see Table B2 in Appendix B.2.

The combined regression models again show that an increase in volatility, using either measure, coincides with an increase in the level of attention towards a particular stock. A one standard deviation increase in $Volatility_t$ approximately correlates with a 1.74 point increase in the SVI. For *LogRange*, a 1% increase correlates with a 1.1 unit increase. Some of the lags of volatility have statistically significant, negative coefficients in the combined models; $Volatility_{t-2}$ is negative in combined models (1) and (2), and $LogRange_{t-1}$ is negative in models (3) and (4). This is discussed in Section 6.

In the combined models, there is little evidence of statistical significance for the liquidity measures, with only model 4 showing some evidence that $\log(Illiq)_t$ is significant at the 5%. This coefficient suggests that a 10% increase the illiquidity ratio corresponds to a 0.05 point increase in the SVI.

Whilst a 10% increase in the 5-day return coincides with a 2.4 point increase, on average across models, in the SVI, 1-day returns seem to have no statistically significant impact. In terms of log(*Volume*), we see that the current week is significant at the 1% level in all four of the combined models. On average, a 10% increase in the daily trading volume correlates with a 0.63 point increase in the index. The first lag of log(*Volume*) is also statistically significant and positive at either the 5% or 10% in all four of the models. Considering only coefficients above the 5% significance level, we see that the coefficients on $\log(Volume)_{t-2}$ are negative in models (3) and (4); a 10% increase in daily trading volume leads to a 1.3 point decrease in the index after 2 weeks.[11]

[11] For the full list of regression coefficients, I refer the reader to Table B2.

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Table 12: Combined Regression Models

	$Attention_t$			
	(1)	(2)	(3)	(4)
$Volatility_t$	121.7839***	125.7509***		
	(12.5112)	(16.7997)		
$LogRange_t$			118.3787***	101.1842***
			(19.032)	(21.5185)
$Spread_t$	2.1243		2.1046	
	(1.4439)		(1.4435)	
$\log(Illiq)_t$		-0.2252		0.5527**
		(0.2982)		(0.2689)
$1DRet_t$	-3.8751	-2.6466	-4.4913	-7.4808
	(25.6738)	(25.7264)	(25.9556)	(25.8730)
$5DRet_t$	22.1644***	20.7105***	27.3421***	27.4927***
	(7.4752)	(7.5374)	(7.5596)	(7.5471)
$\log(Volume)_t$	6.6466***	5.4792***	6.9942***	6.1680***
	(0.4536)	(0.5926)	(0.4679)	(0.5473)
$Attention_{t-1}$	0.2109***	0.2106***	0.2112***	0.2108***
	(0.0076)	(0.0076)	(0.0076)	(0.0076)
$Attention_{t-2}$	0.1761***	0.1760***	0.1754***	0.1751***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)
$\log(Turnover)_t$	-1.1337***	-0.0742	-1.0966***	0.2281
	(0.2061)	(0.5616)	(0.2064)	(0.5013)
$\log(MarketCap)_t$	0.4902***	0.4694***	0.4671**	0.4383***
	(0.1872)	(0.1641)	(0.1888)	(0.1660)
Constant	-68.4804***	-62.3073***	-69.3914***	-60.2172***
	(3.2257)	(4.1247)	(3.2705)	(4.1402)
N	24,534	24,534	24,534	24,534

Note: $\log(Turnover)$ and $\log(MarketCap)$ are weekly averages by stock. ( ) = standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

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5.2 Results by Market Capitalisation

The models in this section use Models 1 through 7 with fixed effects and HAC standard errors, but condition on subsets of the data, namely, quartiles of market capitalization. The tables below report only the coefficients of the variables of interest, however, the regression is run using the full model, including the control variables and lags of *Attention*.

We can see from Table 13 that the coefficients on $Volatility_t$ are statistically significant at the 1% level for all quartiles of market capitalisation. The coefficient on $Volatility_t$ is greater for the top 25% than the bottom 25% at the 5% level (one-sided p-value = 0.044). The coefficients for $Volatility_{t-2}$ are significant at the 5% and 1% levels for the middle 50% and top 25%, respectively, but not for the bottom 25%. The coefficients on $LogRange_t$ are statistically significant for all three groups, and for $LogRange_{t-2}$ in the model conditional on the top 25%. Despite the coefficient being large for the top 25%, the difference between the three groups is statistically insignificant at the 10% level; this suggests that the magnitude of the effect of $LogRange_t$ on $Attention_t$ does not vary with market capitalisation.

Whilst there are no significant results for *Spread* in Table 14, the results show that the coefficients for $\log(Illiq)_t$ are statistically significant across all levels of market capitalisation. For the top 25% of stocks, a 10% increase in illiquidity correlates with a 0.11 increase in the SVI. However, the coefficients are statistically insignificant across levels of market capitalisation, with p-values greater than 10%.

When considering 1-day and 5-day returns using the conditional models (Table 15), we see that the coefficients on $1DRet_t$ are positive and significant for the middle 50% and top 25%, but not for the bottom 25%. As with the models using the complete data set, the coefficients on lags of 1*DRet* are insignificant above the 5% level. The coefficient for the top 25% is statistically greater than for the bottom 25% (one-sided p-value = 0.063). However, the magnitude of the effect for the top 25% is not statistically greater than the middle 50% (one-sided p-value = 0.275).

The coefficients on $5DRet_t$ are positive and significant for the middle 50% and top 25%, but not for the bottom 25%. For the middle 50%, $5DRet_{t-2}$ is significant at the 5% level. The impact for the top 25% is greater than that for the bottom 25% of stocks (p-value = 0.029). Furthermore, I find that the coefficients on $5DRet_t$ for the top 25% and middle 50% are statistically indifferent at the 10% level, however, the magnitude of $5DRet_t$ for the top 25% is greater than that for the overall model in Table 10 (one-sided p-value = 0.049). As with the models using the complete data set, I find that the coefficients for $1DRet_t$ are statistically greater than those for $5DRet_t$ when considering the middle 50% and the top 25% of stocks; the one-sided p-values are 0.014 and 0.027, respectively.

Table 16 shows that the coefficients for $\log(Volume_t)$ are significant across all three groups at the 1% level. The coefficient on $\log(Volume_t)$ is greater in magnitude for the top 25% than for the bottom 25% and middle 50% (one-sided p-values are <0.0001 in both cases). These results suggest that a 10% increase in daily trading volume is associated with a 2.9 point increase in the Google SVI for largest 25% of stocks, but only 1.4 (0.4) points if the market capitalisation of the stock in question is in the middle 50% (bottom 25%).

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Table 13: Conditional Volatility Models - Market Capitalisation

	$Attention_t$		
	(< 25%)	(25% − 75%)	(> 75%)
Model 1			
$Volatility_t$	107.8026***	125.4182***	169.4088***
	(23.5497)	(15.7617)	(27.2237)
$Volatility_{t-1}$	15.7332	15.6350	-21.7287
	(17.7681)	(15.2210)	(22.5849)
$Volatility_{t-2}$	-19.1930	-37.8247**	-78.5462***
	(18.0220)	(16.1672)	(22.8793)
$Volatility_{t-3}$	8.7832	13.5062	-47.1725**
	(18.282)	(14.0192)	(22.2586)
N	5,964	12,496	6,248
Model 2			
$LogRange_t$	90.1998**	125.1812***	126.4181***
	(35.2115)	(19.167)	(36.6571)
$LogRange_{t-1}$	-20.0249	-28.0993	-38.8627
	(20.9006)	(18.4965)	(32.9047)
$LogRange_{t-2}$	-2.7910	-2.9353	-82.2820***
	(20.3983)	(17.4676)	(28.1223)
N	5,985	12,540	6,270

The models above use fixed effects and HAC (Newey-West) standard errors.
*: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$.
( ) = standard errors.

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Table 14: Conditional Liquidity Models - Market Capitalisation

	$Attention_t$		
	$(< 25\%)$	$(25\% - 75\%)$	$(> 75\%)$
Model 3			
$Spread_t$	-27.7814	-459.8807	32.6191
	(392.2514)	(484.5686)	(240.2769)
$Spread_{t-1}$	-353.6316	254.6537	32.8835
	(400.0749)	(450.0512)	(224.0972)
$Spread_{t-2}$	579.7220	-1103.0110*	-188.5224
	(424.1875)	(562.1837)	(144.4238)
$Spread_{t-3}$	569.3762	460.7781	243.3696
	(485.1770)	(480.3467)	(320.8273)
N	5,964	12,496	6,248
Model 4			
$Log(Illiq)_t$	1.4592***	0.7172**	1.0622***
	(0.4923)	(0.3102)	(0.3982)
$Log(Illiq)_{t-1}$	0.0578	0.2786	-0.0627
	(0.4762)	(0.3054)	(0.4073)
$Log(Illiq)_{t-2}$	0.6360	0.3734	0.0480
	(0.4522)	(0.3266)	(0.4064)
$Log(Illiq)_{t-3}$	1.4804***	0.5093	-0.1282
	(0.4840)	(0.3105)	(0.387)
$Log(Illiq)_{t-4}$	0.4325	0.4834	0.5769
	(0.4389)	(0.2980)	(0.3952)
N	5,943	12,452	6,226

The models above use fixed effects and HAC (Newey-West) standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.
( ) = standard errors.

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Table 15: Conditional Returns Models - Market Capitalisation

	$Attention_t$		
	$(< 25\%)$	$(25\% - 75\%)$	$(> 75\%)$
Model 5			
$1DRet_t$	24.7490	63.6720**	83.8709***
	(26.5784)	(18.8736)	(27.9293)
$1DRet_{t-1}$	26.4432	26.3124	14.4953
	(22.3552)	(17.9796)	(26.1269)
$1DRet_{t-2}$	25.6377	31.8878*	10.7152
	(22.3700)	(16.3020)	(24.9886)
N	5,985	12,540	6,270
Model 6			
$5DRet_t$	8.9805	20.4122***	27.9787***
	(6.6562)	(5.3337)	(7.5093)
$5DRet_{t-1}$	6.9665	0.6296	-10.4196
	(5.8489)	(4.2501)	(6.2620)
$5DRet_{t-2}$	1.7721	11.1796**	7.1928
	(5.5259)	(4.4008)	(6.5668)
$5DRet_{t-3}$	0.3212	-2.2792	17.4227**
	(5.4183)	(4.7442)	(6.2387)
$5DRet_{t-4}$	1.8299	6.4657	-4.6227
	(6.1567)	(4.0597)	(6.5831)
N	5,922	12,408	6,204

The models above use fixed effects and HAC (Newey-West) standard errors.
*: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.
( ) = standard errors.

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Table 16: Conditional Volume Models - Market Capitalisation

	$Attention_t$		
	$(< 25\%)$	$(25\% - 75\%)$	$(> 75\%)$
Model 7			
$Log(Volume)_t$	4.5007***	14.2636***	29.4081***
	(0.8494)	(0.6747)	(1.4165)
$Log(Volume)_{t-1}$	1.2581	-0.1867	0.3602
	(0.8789)	(0.5749)	(0.8483)
$Log(Volume)_{t-2}$	-0.9755	-1.5833***	-2.4893***
	(0.8544)	(0.5925)	(0.9050)
$Log(Volume)_{t-3}$	-0.4076	0.0330	-0.8914
	(0.7542)	(0.4942)	(0.8048)
N	5,964	12,496	6,248

The models above use fixed effects and HAC (Newey-West) standard errors.
*: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$.
( ) = standard errors.

6. Discussion

Firstly, we must consider the extent to which we can identify causality in these results, that is, the extent to which the market dynamics discussed cause increased retail investor attention. There may be a bi-directional relationship between retail investors and the market dynamics in question; Welch (2022) suggests that, whilst retail investors may be a cause of increased volatility, they may also be attracted by it, adding to the complexity of identifying the direction of the effect. One may hypothesise that an increase in the number of traders may increase volatility, which could in turn, attract more retail investors. Similarly, those investors that are attracted by higher price returns may, in turn, contribute to increased stock prices through increased purchasing. A similar case could be made for higher trading volume attracting investors' attention, leading to more trading in that stock. However, by accounting for the lags of both *Attention* and the variables of interest, that is, if the model is correctly specified, one should be able to identify, to a certain degree, the effect of such a loop. Thus, if the feedback effects are accounted for, the remaining effects, unless affected by other factors, should be the causal impact of the variable of interest on attention.

The positive coefficients for both $Volatility_t$ and $LogRange_t$ suggest that an increase in volatility coincides with increased investor attention. One economic interpretation for a causal relationship is that more volatile markets offer the potential for higher returns and short-term profits, incentivizing retail investors to trade. Furthermore, more volatile stocks are likely to attract media attention; the more volatile the stock, the greater the price fluctuations, which, in turn, increases the likelihood that this stock is discussed in the media. Increased investor attention will likely follow from this increased media attention. An additional explanation for a causal effect is the idea of risk-seeking behaviour among retail investors; Grinblatt and Keloharju (2009) identifies 'sensation-seeking' behaviour as an motivation for retail trading. Hence, more volatile stocks offer higher risks and rewards, appealing to some investors.

From the empirical results, the relative spread models are largely statistically insignificant. However, this is more likely a limit of the data than the true correlation, especially when the Amihud illiquidity measure shows statistical significance. With access to intra-day bid-ask spread data, the statistical power would be improved. There is evidence that periods of lower liquidity correlate with increase attention, as evidence by the positive coefficients on $\log(Illiq)_t$. This is the case in the individual models, as well as some evidence being seen for this in the combined models. The market capitalisation models also show significant results for this. However, it is more likely that these are correlated with a market event rather than the effect of liquidity itself. For example, we saw a drastic decrease in market liquidity at the start of the COVID-19 pandemic, which also brought significant attention to markets. Retail investors replaced much of this liquidity when institutional investors were constrained (Ozik et al., 2021; Pagano et al., 2021).

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It would be difficult to say, however, that liquidity itself was a driver of this retail investors trading and attention.

I find strong evidence that increased returns lead to increased investor attention, as suggested by the positive results for $1DRet_t$ and $5DRet_t$. De Bondt (1993) documents that retail investors "expect the continuation of apparent past trends in prices"; this extrapolation likely leads retail investors to become attracted to a stock, believing that it will be an opportunity to earn the same returns that they have just observed. Furthermore, extreme returns are often widely covered by the media, which would translate into increased attention. The impact of returns on attention may also be causal due to the peer effect (Kaustia and Knu¨pfer, 2012); peers earning high returns from a stock would likely incentivise other retail investors to focus their attention on this stock, leading to them trading it.

Table 15 shows that the effect for the top 25% of stocks is greater than for the bottom 25%, suggesting that, for an increase in returns of equal size, the larger stocks attract more investor attention; I put forward two potential reasons for this. Firstly, stocks with larger market capitalisation naturally attract more media attention, given that they are more 'important' in the composition of the FTSE 100. Hence, an increase in the returns for larger stocks is more likely to be discussed. Secondly, stocks with higher market capitalisation are less volatile,[12] and, hence, a significant jump in daily return for a stock in the top 25% is likely to capture more attention.

The results suggest that daily trading volume may also cause an increase in retail investor attention, as evidenced by the positive coefficients of $\log(Volume)_t$. One hypothesis for this may be that retail investors like to trade similar stocks to both their peers and to other retail investors in general; there have been extreme cases of this, such as the GameStop episode and the trading of 'meme stocks'. Retail investors may suffer from confirmation bias; they could already be aware of a stock but a large increase in trading volume may confirm that their stock is popular, given that others are trading it. However, it may not be possible to identify an entirely casual relationship between volume and attention. Increased trading volume often coincides with stock events, such as earnings announcements, which makes it difficult to disentangle the impacts of trading volume from the stock event on attention. As such, the extent to which higher trading volume *causes* increased retail investor attention remains unclear; to disentangle these effects, an analysis around stock events using more accurate, intra-day data would be a good starting point.

An interesting observation from the results is the short-run nature of the effects of market dynamics, as evidenced by the either negative or insignificant lags of volatility, returns, and trading volume. $Volatility_{t-2}$ and $LogRange_{t-1}$ both have negative coefficients, suggesting that attention has already fallen approximately two weeks after a shock to volatility, potentially reverting towards the mean. For both 1-day and 5-day returns, shocks at time $(t-1)$ are insignificant (beyond the 10% level) for $Attention_t$; only a shock to returns in week t appears to impact attention. For log(*Volume*), we see that the coefficient is insignificant for the first lag and negative for the second. These results collectively suggest that the attention of retail investors may be primarily short term, with prior shocks to dynamics having little effect.

[12] Using the standard deviation measure of volatility (Equation (1)), I find that the volatility for the top 25% (0.0171)

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7. Conclusion

In this paper, I analyse the impact of changes in markets dynamics (volatility, liquidity, returns, and trading volume) on UK retail investor attention, as measured by the Google SVI. Using a sample of 87 stocks from the FTSE 100 index, I run regression models on both the entire data set, and on subsets of the data, filtered by market capitalisation, to identify potentially heterogeneous effects.

Overall, I find that changes in volatility, returns, and, to some extent, daily trading volume lead to increased retail investor attention in UK markets. Whilst liquidity is negatively correlated with attention, that is, more illiquid stocks attract greater attention, this is likely due to the liquidity-reducing events, such as the COVID-19 market shock. The effects of increased returns and trading volume are more pronounced for the top 25% of stocks by market capitalisation than for the bottom 25%..[13]

I hypothesise that the positive effect of volatility could be due to increased media attention, retail investors seeking short-term gains, or sensation-seeking behaviour. For returns, amongst other reasons, this effect may be due to extrapolation of past returns, with investors expecting that they can earn similar returns. One reason for the impact of trading volume is due to confirmation bias; seeing other investors trade stocks that they have considered may encourage them to follow them to follow the stock more closely. However, it is difficult to identify a purely causal relationship as there exist issues in disentangling the impact of trading volume from a stock event.

A point of interest is the short-term attention of retail investors evidenced in the data. The lags of many of the market dynamics variables are either negative or insignificant, suggesting that, after the current week, these dynamics have little effect on the attention of these investors. These investors are quick to react to changes but their attention not be sustained over periods of more than one week.

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[13] is statistically smaller in magnitude than for the bottom 25% (0.0193) (one-sided p-value < 0.001), as calculated using Welch's t-test.

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Guest Features

The UCL Journal of Economics serves as an institution for students across the world to showcase their research and undergo a rigorous peer-review process. Here, we are grateful to present three exceptional articles from students at Harvard University, the University of Notre Dame, and University College London.

Article

Racial and Ethnic Disparities in Maternal Treatment and Death: Evaluating the Role of Hospital and Physician Effects

Maura Rose Hogaboom[1]

[1] Student, Dept. of Economics, University of Notre Dame, USA; mhogaboo@nd.edu

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Abstract

Past work has documented disparities in medical treatment and health outcomes across racial and ethnic groups. In some instances, disparities persist beyond individual health risk factors and reveal underlying differences in the hospital facilities or the attending physicians that different patients tend to go to. In the case of maternal mortality and cesarean delivery, not only does the U.S. perform poorly on both measures, but also there exist racial and ethnic disparities in maternal treatment that lead to disadvantaged outcomes for vulnerable populations. By separately absorbing hospital and physician fixed effects, the contribution of both facility and practitioner variation to the present health disparities can be identified. Hospital variation maps to a significant portion of the racial disparity in cesarean delivery and the ethnic disparity in the induction of labor. Controlling for physician fixed effects explains some portion of the racial disparities in maternal mortality and cesarean delivery, all of the ethnic disparity in cesarean delivery, and some of both disparities in the induction of labor. These results suggest ample opportunities for targeted intervention to minimize the variation between physicians and hospitals in their approach to maternal care toward more equitable care provision.

Keywords: Maternal Mortality, Maternal Health, Health Disparities, Fixed Effects

1. Introduction

Despite significant improvements in healthcare across the United States and the developed world over the last century, United States maternal mortality rates are by far the highest among its peer countries. In 2018, the United States reported 17 maternal deaths per 100,000 live births, about six times the rate in countries such as the Netherlands and New Zealand (Tikkanen et al., 2020). Within the U.S., there also exists a significant disadvantage in maternal outcomes for Black individuals and other minority populations within the country. In 2020, the U.S. National Vital Statistics System reported that within the United States, the maternal mortality rate for non-Hispanic Black women was 55.3 deaths per 100,000 live births, a value 2.9 times the rate experienced by non-Hispanic white women (Hoyert, 2022). While the overall maternal mortality rate for Hispanic populations is not as disparate from that of non-Hispanic white populations, both racial and ethnic disparities in maternal treatment are similarly disparate.

The United States operates a hybrid health system consisting of publicly financed health coverage like Medicare and Medicaid, privately financed coverage like private health insurance, and out-of-pocket payments ("US Healthcare System"). Similarly, hospitals receive both public and private funding in amounts based upon the specific condition or treatment of a given patient ("US Healthcare System"). Because complicated and varied health schemes overlap with social concepts like race and other cultural and political institutions, causes of racial and ethnic disparities are inherently difficult to identify and eradicate. The United States has not only higher rates of unhealthy behaviors in calorie consumption and drug misuse but also maintains a built environment that discourages physical health and is racially and socioeconomically segregated (Crear-Perry et al., 2021). The difference in maternal mortality and treatment outcomes between racial and ethnic groups could arise due to differences in observed characteristics. Comorbidities and disease incidence tend to impact vulnerable populations at higher rates, placing them at higher risk for health complications (Ahmed et al., 2020). Beyond individually observable conditions like obesity or Medicaid coverage, disparities in health outcomes could emerge from differences in treatment patterns. Individuals of different racial and ethnic groups may seek–or be able to seek–treatment at starkly different facilities or from different healthcare professionals. Many individuals in the United States suffer due to the inaccessibility of care whether due to financial limitations or a dearth of primary care providers (Crear-Perry et al., 2021). The impacts on health outcomes of lower income, insurance coverage, and lack of access to care reveal the poverty-related limitations disproportionately felt by communities of color. Between healthcare facilities like hospitals, even if the medical practitioners themselves are similar, access to resources and funding, as well as institutional practices, could impact treatment practices. If it is the case that physicians themselves are fundamentally different, variation in cultural competency or implicit bias could impact the treatment of vulnerable populations.

Previous studies have explored to what extent observed characteristics determine health disparities. Ultimately, individual-level variation in medical risk factors, income, educational attainment, and insurance status do not explain the extent of health access, treatment, and outcome disparities across racial and ethnic cohorts (Gavin et al., 2004; Kirby et al., 2006). Others have shown that Black and Hispanic patients are treated at lower-performing hospitals and that hospital variation contributes to disparities in mortality (Chandra et al., 2020). Similarly, physician biases in diagnosis and treatment determinations can impact Black patients' health outcomes, including survival (Eli et al., 2019). Other literature analyzes both contributing factors in hospital and physician variation, attempting to explain disparities in the mortality treatment patterns of racial groups (Greenwood et al., 2020; Lee et al., 2019; Peterson et al., 1994; He et al., 2012; Popescu et al., 2016; Barnato et al., 2006). Overall, there is well-documented descriptive work of disparities in health and ample efforts to identify their point of emergence within the healthcare system for multiple health concerns. However, no study has tested physician and hospital variation to determine their contribution to well-established disparities in maternal treatment and outcomes for racial and ethnic cohorts.

I begin to identify the ways in which racial and ethnic disparities emerge in the United States healthcare system by disentangling the roles of hospital-level variation and physician-level variation in maternal death, cesarean delivery, and the induction of labor. Using Florida inpatient hospital census data of individual-level hospitalization instances from 2006 to 2014, I use multiple linear probability models which exploit variation in race and ethnicity among patient observations to estimate the disparate rates of maternal death non-Hispanic Black, non-Hispanic white, and Hispanic population cohorts. Two nearly identical models use the same changes in race and ethnicity to estimate the disparities in instances of cesarean delivery and the induction of labor in the sample. By absorbing fixed effects for hospitals and physicians separately in each of these estimations and controlling for individual characteristics including comorbidities, age, insurance status, and socioeconomic status (SES) indicators in recorded zip code, I identify the partial contribution of hospitals and physicians toward the observed racial and ethnic disparities in maternal health. In the identification of the level, hospital or physician, at which these disparities emerge, there arise opportunities for eliminating the preventable deaths of Black mothers. Whether by altering hospital culture and funding allotments or transforming physician training practices, targeted interventions can attempt to minimize emergent disparities. If patients nonrandomly sort to hospitals and physicians, then variation in hospitals and physicians will explain some portion of racial and ethnic disparities in maternal death and treatment.

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2. Background

2.1. Racial Disparities

Despite the tremendous improvements in healthcare and health outcomes in the U.S. over the past century and a quarter, not all groups of the population experienced the same level of benefit. Racial and ethnic inequalities that permeate the United States' economy, society, and culture also appear in healthcare access, treatment, and outcomes. Racialization and ethnicization are processes that ascribe social meaning to observable characteristics. Historically, as those social meanings are assigned, hierarchies emerge in which dominant groups are able to maintain power and as a result, constraints exert themselves on the resource access of socially devalued groups (Hicken et al., 2018). One such social constraint lies in the creation of generalized archetypes such as a Black individual who has engaged with the criminal justice system or a Hispanic individual who is an undocumented immigrant. This type of cultural stereotyping formulates "spillover effects" that impact other members of the social group through stigmatization and resultant implicit biases (Hicken et al., 2018). Racial and ethnic biases in research and practice recommendations, especially in the field of healthcare, are characterized by a lack of individuals of color as subjects and participants as institutions of higher education systematically exclude people of minority backgrounds (Graves, 2019).

In healthcare, vulnerable populations are described as "social groups who experience limited resources and consequent high relative risk for morbidity and premature mortality" (Flaskerud, 1998). Thus, as resource access and biases combine to create disadvantaged health outcomes for vulnerable populations, race and ethnicity have real biological effects not because of true genetic or natural differences, but because of socially constructed and maintained differences. Those socially constructed and maintained differences in U.S. culture have their deep roots in the time of slavery when our nation's institutions were being built upon the assumed supremacy of dominant white male landowners. For vulnerable populations today, modern day health disparities partially arise from practices built upon ideologies of racial difference originating from a time when Black individuals were not recognized as genetic or social equals. The idea that black people have lower lung capacity, higher heat and pain tolerance, higher disease tolerance, and mental deficiency have very serious effects as doctors tend to treat patients differently according to these implicit biases (Hammonds et al., 2019). While more recent years have called more direct attention to racial and ethnic disparities in healthcare, the 2002 Kaiser Family Foundation National Survey of Physicians found that a majority of doctors say that the healthcare system rarely (55%) or never (14%) treats people differently based upon racial or ethnic background ("National Survey", 2002). When considering well-documented differences in treatment, it becomes evident that implicit bias remains an aspect of healthcare influencing today's disparate outcomes for vulnerable populations.

2.2. Racism in Maternal Healthcare

Specifically in the field of obstetrics and gynecology (OBGYN), its founding and development with early researchers relied on experimentation on enslaved women, seeking to control their reproduction (Rubashkin, 2022). These origins in subjugation create a systemic and lasting bias against communities of color and other vulnerable populations that are forced to exist within systems built upon their exploitation. For example, the National Institute of Child Health and Human Development Maternal-Fetal Medicine Units Network formulated a decision-making algorithm based upon the probable success of a vaginal birth after a cesarean delivery (VBAC), which is a decision that arises when a birthing mother previously underwent a primary cesarean and may be a candidate for a subsequent vaginal birth. It is a national public health interest to increase successful VBACs because multiple surgical births are riskier for the mother (Rubashkin, 2022). The VBAC algorithm automatically predicts approximately half of the probable success for minority women, assuming intrinsic racial differences and ignoring the fact that racism and biases, not race and ethnicity themselves, generates disparate health outcomes (Grobman et al., 2007). Even in removing the explicit discount for Black and Hispanic women, they are differentially likely to be subject to the delivery via cesarean when comorbidity incidence rates like obesity and hypertension rates are differentially high among minority populations. It is important to note that in the case of maternal morbidity–health problems arising from pregnancy and childbirth–racial and ethnic disparities in maternal health treatment patterns seem to transcend any socially disparate instances of comorbidities (Admon et al., 2018).

On a global scale, the Millennium Development Goals put forth by the United Nations sought to reduce maternal mortality by 75% by 2015 (MacDorman et al., 2016). Despite these international healthcare development ideals, the maternal mortality rate in the United States has increased in recent years, and, in fact, the unadjusted rate of maternal mortality more than doubled between 2000 and 2014 (MacDorman et al., 2016). A portion of these increases arise from changes in reporting seeking to make the collection of maternal mortality data more accurate, but even when accounting for previous underreporting, there exists a 26.6% increase in maternal mortality between 2000 and 2014 (MacDorman et al., 2016). The present racial and ethnic imbalances in healthcare and health outcomes are glaringly evident in the disparities defined in measured maternal mortality and maternal care outcomes. Further, in comparing the maternal mortality rates between 2019 and 2020, the increases in rate for non-Hispanic Black women was statistically significant while the relatively smaller increases experienced by non-Hispanic white women were not significant (Hoyert, 2022).

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Figure 1 displays the mortality due to pregnancy, childbirth, and the puerperium, which is the period of six weeks following childbirth, per 100,000 live births by race according to compressed mortality data by the Centers for Disease Control and Prevention ("Compressed Mortality File", 1980; "National Vital Statistics" 1980). Over the forty years reported, the mortality rate remained constant until 2000, at which point it began increasing. The rate of Black mortality in Figure 1 is significantly greater than that of white populations, and in recent years, it increased at an accelerated rate.

Figure 2 displays these same mortality measurements for Hispanic and non-Hispanic white groups ("Compressed Mortality File", 1999; "National Vital Statistics" 1980). Collection of data on ethnicity began in 1998 in the U.S., so Figure 2 describes Hispanic and non-Hispanic mortality rates from 1999 until 2020. In 2000, the mortality rates due to pregnancy, childbirth, and the puerperium were nearly identical but subsequently began to diverge over the following decades. Contrary to the divergent increase in Black population mortality, the mortality rates of Hispanic people increase at a slower rate as compared to those of non-Hispanic white populations. This parallels the "Hispanic health paradox" which describes the fact that Hispanic people in the U.S. tend to experience health outcomes in parity with or better than other social groups in measures of life expectancy, infant mortality, cancer morbidity, and other health measures despite having lower income and lower rates of insurance coverage (Fernandez et al., 2023). On a national scale, a younger age at childbirth for Hispanic parents and lower rates of engagement in risky health behaviors like smoking could contribute to these mortality outcomes (Fernandez et al., 2023).

Like the United States' shortcomings in maternal mortality, "the primary cesarean rate was 21.5% in 2005 and the overall rate reached 32.9% in 2009" (Solheim et al., 2011). These rates greatly exceed the maximum 15% cesarean rate recommended by the World Health Organization (Solheim et al., 2011). Delivery via cesarean raises the relative risk of maternal mortality, and Black and Hispanic patients have much higher rates of delivery by cesarean. In 2021, 30.8% of births to white patients were cesarean deliveries as compared to 31.3% of deliveries to Hispanic patients and 36.2% for Black patients ("Final Natality", 2021). Another common treatment in labor management is the induction of labor (IOL), which includes the rupturing of membranes or medical or surgical intervention to initiate labor. Like cesarean delivery, the rates of IOL are stratified by racial and ethnic groups. Black and other minority patients have lower rates of IOL than white populations, as shown in a 2021 study which found that in the U.S., 27.2% of Black patients experienced IOL compared to 32.5% of white patients (Singh et al., 2018; Wang et al., 2021). Though the medical necessity of IOL in varying contexts of parental age, gestational age, and other characteristics should be considered by medical practitioners, the general professional guidelines suggest that IOL can be used to reduce the likelihood of cesarean delivery (Hamm et al., 2020). So, it is evident that racial and ethnic differences in the rates of both cesarean delivery and IOL align with other documented health disparities in treatment and outcomes.

3. Literature Review

In this study, I focus on identifying the contribution of hospitals and physicians to the present racial and ethnic disparity in maternal death, cesarean delivery, and IOL. While little research exists surrounding maternal health beyond the provision of summary statistics, previous literature has identified the contribution of hospital variation and physician bias to disparities in other health outcomes. Using Medicare hospitalization records and enrollment records, one study establishes a method of measuring hospital performance using survival rates and calculates that rate for Black and white populations (Chandra et al., 2020). They then demonstrate that Black heart attack patients go to lower performing hospitals even when living in the same Hospital Referral Region as comparable white patients. The racial disparity in outcomes has been diminishing in more recent years with improvements characterized by the adoption of technologically advanced treatment techniques concentrated at low performing hospitals treating mostly Black patients (Chandra et al., 2020). A separate study estimates the racial disparity in lifespan outcomes for Union Army veterans by exploiting existing variation in physician disability ratings in their determinations which impact disability insurance provision. Their work confirms an impact of physician attitudes on racial disparities in health based upon the fabricated ideas of the inferiority of the Black body and of the lesser status of symptoms experienced by those bodies, significantly impacting the outcomes of health concerns which are difficult to uniformly diagnose (Eli et al., 2019).

There is also evidence that utilizes a census of patients admitted to hospitals in the state of Florida that includes individual-level data on race, comorbidities, and patient outcomes, as well as hospital and physician identifiers. The data confirm a disadvantage in mortality for Black mothers, and specifically that Black mothers attended by white physicians "experience an additional 14 deaths per 100,000 births, tripling white mothers' mortality rate of 7 per 100,000 births" (Greenwood et al., 2020). Despite this documented disparity, racial concordance does not provide statistically significant change in mortality for Black mothers.

Another group of studies attempt to identify the emergence of racial disparities in the intensity of treatment for various health issues. Lee et al. (2019) explores the effect of being from a minority group on the use of pain treatment medications for acute pain presentations in emergency department settings. They find that Black patients and Hispanic patients were less likely than white patients to receive equivalent pain management use. Peterson et al. (1994) find that Black patients with acute myocardial

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infarction are less likely to undergo intensive treatment. He et al. (2012) update and expand upon these findings and demonstrate that controlling for hospital and physician fixed effects can explain the Hispanic-white disparities and some of the Black-white disparities existing across surgical treatment techniques for patients experiencing acute myocardial infarction. They outline many of the avenues by which such racial and ethnic disparities may emerge at either the hospital or physician level as minority patients may obtain treatment from specific hospitals or physicians via mutual selection. The control variables utilized in their model are paragon as they not only match patient discharge to socioeconomic status data for further individual-level controls, but they also match hospital identifiers to factors such as hospital ownership type and teaching status.

Similarly, Popescu et al. (2016) suggest that a portion of the racial and ethnic disparities present in care for colorectal and breast cancer patients is attributable to physician-level variation. Using physician fixed effects in a logistic model to evaluate the effects of race, ethnicity, and socioeconomic status on cancer care quality, the study found that minority and low socioeconomic status patients are less likely to receive any of the recommended cancer treatments. Barnato et al. (2006) use a similar fixed-effect model to study terminal admissions across multiple states, arguing that racial disparities in individual treatment preferences cannot create all of the disparity in end-of-life care since preferences rarely map to exact treatment outcomes. They demonstrate that racial and ethnic disparities in end-of-life care emerge from hospital-level variation in ICU use, and those differences do not emerge within hospitals themselves. In accordance with this body of literature which utilizes hospital and physician variation to identify their relative contribution to disparate treatment and mortality outcomes along lines of race and ethnicity in pain management, AMI, cancer, and end-of-life care, I evaluate these hospital- and physician-level contributions toward racial and ethnic disparities in maternal death, caesarean delivery occurrence, and IOL.

4. Data

This study uses hospital inpatient census data from 2006 to 2014 from the Agency for Health Care Administration in the state of Florida. Each record has data on patient race, ethnicity, age, zip code, principal payer, procedures performed, neonatal ICU charges, up to thirty comorbidities, and the disposition of the discharge (e.g., patient discharged to home, transferred to another hospital, patient expired, etc.). The sample was limited to patients who delivered a child during that time period[1]. I further limited the sample to patients whose race was either Black or white or whose ethnicity was Hispanic. These sample limitations yielded a sample of 1,589,374 hospitalization instances for analysis. The key explanatory variable is based upon the patient's race and ethnicity to create population cohorts of non-Hispanic Black patients, Hispanic patients, and non-Hispanic white patients.

The outcomes of interest are whether the patient died in the hospital, whether the delivery was by cesarean section or there was IOL. Maternal death occurrence is defined by the discharge status of, which provides a limited definition of maternal mortality that does not include patients who die outside of the hospital or in subsequent hospitalizations. Cesarean delivery occurrence is obtained from the Medicare diagnosis-related group (DRG) (Fingar, 2006) and the applicable procedure codes according to the International Classification of Disease Vol. 3 Procedure Codes (ICD-9-CM) ("ICD-9-CM Diagnosis")[2]. Similarly, IOL occurrence is obtained from the procedure codes of ICD-9-CM ("ICD-9-CM Diagnosis")[3].

I utilized numerous control variables from the individual-level hospital records for the resulting multivariate analysis. I used a continuous measure of age to account for the relationship between increasing age and increasing maternal mortality and treatment interventions. Similarly, age-squared accounts for the fact that the impact of age on outcomes of interest may vary over the range of ages in the sample. I controlled for certain comorbidities that play a role in maternal mortality and treatment outcomes including obesity, diabetes, hypertension, asthma, hypothyroidism, cord complications and smoking. I created indicator variables for each instance of these comorbidities according to their ICD-9 diagnosis codes ("ICD-9-CM Diagnosis").

[1] Patients who delivered a child during that time period are identified by the patients that experienced charges for labor and delivery room services according to revenue codes 720 through 729 outlined by UB-02 and UB-04 and used for uniform medical billing across medical institutions.
[2] DRG codes were recorded until the fourth quarter of 2007 when the records were refined to groupings according to Medicare Severity (MS) DRG codes. Cesarean delivery occurrences are identified by DRG 370 and 371 prior to 2007, by MS-DRG 765 and 766 after 2007, and by ICD-9-CM 74.00-74.99 for the entire time period.
[3] IOL occurrences are identified by ICD-9-CM 73.00-73.99 for the entire time period.

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Additionally, I controlled for time-variant effects using indicator variables for the quarter and year of the hospitalization instance.

I used each patient's zip code of residence to match each hospitalization record with median household income using data from the American Community Survey administered by the U.S. Census Bureau. This serves as a continuous measure of socioeconomic status of patients at the zip code-level since personal income data is not attainable. The American Community Survey data did not include zip code-level median household income prior to 2011. Since the data at this level of geography is only available as a five-year average and zip code-level socioeconomic indicators are unlikely to dramatically change within a short period, I used the 2011 median household income across the entire sample.

A unique feature of the Florida inpatient dataset is that it has a code for each facility and attending physician, and I used these codes to control for hospital and physician fixed effects. The facility code is the Agency for Health Care Administration facility number which allowed me to then match each record to observed hospital characteristics using the Centers for Medicare & Medicaid Services Provider of Service 2011 dataset ("The Provider of Services", 2011). From this data, I obtain hospital-level urbanity, ownership, and bed count.[4]

5. Methods

I used Stata/BE 17.0 as an analysis software to perform a multivariate analysis using a set of twelve linear probability models with varying fixed effect controls to estimate the marginal effects of group-specificity on outcomes of interest. The central estimating equation takes the form of a linear probability model illustrated by equation [1].

$$Y_{ihpq} = \beta_0 + race_{ihpq}\beta_1 + ethnicity_{ihpq}\beta_2 + X_{ihpq}\beta_3 + \lambda_q + \epsilon_{ihpq} \qquad [1]$$

The outcome variable of interest Y_{ihpq} takes the form of an indicator variable whether individual i in a hospital h with an attending physician p in year and quarter q expired in the recorded hospitalization. The same applies for an outcome variable of interest in which the indicator variable Y_{ihpq} describes cesarean delivery or IOL at the same levels of specificity. Therefore, I estimated this equation separately for three different outcome variables. The explanatory variable $race_{ihpq}$ is a binary variable indicating whether an individual i in a hospital h with an attending physician p in year and quarter q is Black, and $ethnicity_{ihpq}$ is a binary variable indicating whether an individual i in a hospital h with an attending physician p in year and quarter q is Hispanic. X_{ihpq} a large set of individual-level characteristics for age, zip code-level median household income, primary payer, length of hospital stay, and seven comorbidities associated with maternal health. λ_q controls for the time-variant fixed effects associated with all patients each year and quarter time frame. ϵ_{ihpq} is the idiosyncratic error term which catches all other unobserved characteristics. Overall, β_1 and β_2 are the estimated coefficients of interest which represents the baseline linear probability outcomes, or the marginal effect of an individual patient being Black or Hispanic on mortality, cesarean delivery, and IOL outcomes. This coefficient was later compared to the coefficient of interest arising from equations [2] and [3] which control for hospital and physician fixed effects, respectively, in either race or ethnicity population cohort.

I estimated a nearly identical linear probability model with the addition of hospital fixed effects as encapsulated by equation [2].

$$Y_{ihpq} = \delta_0 + race_{ihpq}\delta_1 + ethnicity_{ihpq}\delta_2 + X_{ihpq}\delta_2 + \alpha_h + \lambda_q + \epsilon_{ihpq} \qquad [2]$$

These hospital fixed effects are described by α_h and in appending them to [1], I am able to absorb all time-invariant characteristics shared by all patients with a hospitalization instance at a given hospital h, including variables that are unobserved in the data. Equation [2] continues to control for individual characteristics (X_{ihpq}) and time-variant effects (λ_q). The estimated coefficients of interest are δ_1 and δ_2 which describes the marginal effect of an individual patient being Black or Hispanic on mortality, cesarean delivery, and IOL outcomes when controlling for hospital fixed effects.

[4] Not all facility numbers in the Florida data matched to a Medicaid or Medicare vendor number, so hospital-level monthly live birth records and facility county were used to match facilities to likely vendor numbers ("Table 14A").

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Third, I estimated another nearly identical linear probability model substituting hospital fixed effects for physician fixed effects shown by equation [3].

$$Y_{ihpq} = \gamma_0 + race_{ihpq}\gamma_1 + ethnicity_{ihpq}\gamma_2 + X_{ihpq}\gamma_3 + \theta_p + \lambda_q + \epsilon_{ihpq} \quad [3]$$

The physician fixed effects are described by θ_p and control for all time-invariant characteristics associated with a specific physician p which would impact all outcomes of patients seen by that physician, including those unobservable in the data. Equation [3] continues to control for individual characteristics (X_{ihpq}) and time-variant effects (λ_q). The estimated coefficients of interest are γ_1 and γ_2 which describes the marginal effect of an individual patient being Black or Hispanic on mortality, cesarean delivery, and IOL outcomes when controlling for physician fixed effects.

Finally, I estimated a model intended for comparison with equation [2] in which the hospital fixed effects, which control for all time-invariant hospital characteristics both observable and unobservable, are replaced with observable hospital characteristics. This linear probability model is described by equation [4].

$$Y_{ihpq} = \mu_0 + race_{ihpq}\mu_1 + ethnicity_{ihpq}\mu_2 + X_{ihpq}\mu_3 + \Psi_h\mu_4 + \lambda_q + \epsilon_{ihpq} \quad [4]$$

Ψ_h is a large set of hospital-level characteristics for facility bed count, urbanity, hospital ownership status, and the presence of a neonatal ICU level I, II, or III. Equation [4] continues to control for individual characteristics (X_{ihpq}) and time-variant effects (λ_q). The estimated coefficients of interest are μ_1 and μ_2 which describe the marginal effect of an individual patient being Black or Hispanic on mortality, cesarean delivery, and IOL outcomes when controlling for observable hospital characteristics.

6. Results

6.1. Descriptive

Table 1 provides the means of variables of interest for the full sample and by race and ethnicity cohorts. As is displayed, the full sample is made up of 1,589,374 patients. There are 809,898 non-Hispanic white patients (51.0%), 387,609 non-Hispanic Black patients (24.4%), and 391,867 Hispanic patients (24.7%). The rates of mortality, cesarean delivery, and IOL suggest racial disparities in all outcomes of interest and ethnic disparities in cesarean delivery and IOL. Across the entire timeframe of the sample, the rate of maternal mortality for non-Hispanic white patients is 0.0054%, 0.0165% for non-Hispanic Black patients, and 0.0046% for Hispanic patients. In this sample, Black patients are much more likely to die in childbirth as indicated by the present odds ratio of approximately 3.2. Figure 3 describes these rates of maternal death in terms of deaths per 100,000 live births across the entire time frame. These rates of maternal death are lower than the U.S. rates for the same timeframe displayed in Figure 1 because the measure of maternal death in these estimates only catch deaths that occur immediately in the initial hospitalization. Figure 4 shows the rates of cesarean delivery for all three population cohorts, and Figure 5 shows the rates of IOL for the same cohorts. Both figures indicate that the difference between the rates of non-Hispanic Black patients and Hispanic patients are significantly different from those of non-Hispanic white patients.

The remaining content of Table 1 summarizes differences in patient characteristics by race and ethnicity. There is a statistically significant difference in all variables listed except for diabetes in Hispanic populations, which trends similarly to non-Hispanic white populations in this sample. Overall, this suggests that non-Hispanic Black and Hispanic patients are slightly younger, have lower median household income, experience longer hospital stays, and are more likely to be on Medicaid or be self-payers than non-Hispanic white patients. Similarly, non-Hispanic Black patients are more likely to be obese, have diabetes, have hypothyroidism, and have asthma than white patients. Non-Hispanic white patients are more likely to have commercial insurance coverage, experience cord complications, smoke, and have hypertension.

Overall, the rates of the comorbidities related to pregnancy and birth risks are much lower in this sample than are found in the broader population. The Pregnancy Risk Assessment Monitoring System (PRAMS) is a state-level surveillance system of maternal health behaviours that seeks to inform prenatal health programs ("Florida Pregnancy"). In the state of Florida, the PRAMS trends over the period 2000 until 2011 found rates of obesity to be near 30% among non-Hispanic Black patients and 20% among non-Hispanic white and Hispanic patients, which are significantly higher than the rates of obesity observed in the Florida inpatient census. Not only did the Florida PRAMS data show that non-Hispanic Black patients experienced a higher

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prevalence of obesity and other comorbidities than non-Hispanic white patients and Hispanic patients, but it also found later entry into prenatal care and lower infant birth weights among that cohort ("Florida Pregnancy").

Because patients from different population cohorts may interact differently with hospitals and physicians, I provide some summarization of the hospitals and physicians within the sample. There are a total of 131 unique hospitals and 4,158 unique physicians, and many physicians see patients at multiple hospitals. This signals that the hospital fixed effects relate to physician fixed effects by providing fixed effects at a more aggregate scale. Similarly, there are 1,225 physicians that only see white patients, 502 physicians that only see Black patients, and 343 physicians only see Hispanic patients. Most of these hospitals and physicians that are only related to one race are only linked to one or very few patients, so this should be understood in describing the hospital and physician data.

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Table 1. Descriptive Statistics for Full Sample and by Population Cohort

Variable	Non-Hispanic White	Non-Hispanic Black	Hispanic	Full Sample
Maternal Death	0.0000543	0.000165***	0.0000459	0.0000793
Cesarean Delivery	0.277	0.287***	0.309***	0.288
Induced Labor	0.676	0.660***	0.653***	0.666
Age	27.89	26.04***	27.53***	27.35
Median Household Income	51237.0	41814.6***	47428.7***	48006.9
Obesity	0.0248	0.0454***	0.0242*	0.0297
Diabetes	0.00696	0.0123***	0.00707	0.00829
Hypothyroidism	0.00576	0.0163***	0.00532***	0.0153
Asthma	0.0318	0.0364***	0.0258***	0.0314
Hypertension	0.0204	0.00488***	0.0148***	0.00822
Smoking	0.00719	0.00222***	0.000972***	0.00444
Cord Complications	0.226	0.193***	0.212***	0.214
Length of Stay	2.612	2.930***	2.685***	2.708
Medicaid	0.414	0.679***	0.591***	0.524
Commercial Insurance	0.518	0.249***	0.298***	0.398
Self-pay	0.0295	0.0329***	0.0674***	0.0397
N	809,898	387,609	391,867	1,589,374

*Statistically significant differences in mean between NH Black and NH white or between Hispanic and NH white indicated by *** for .01, ** for 0.05, * for .10.*

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Table 2. Baseline Linear Probability Model Estimations of Outcomes of Interest

Explanatory Variables	Maternal Mortality	Cesarean Delivery	Induction of Labor
Patient Characteristics			
NH Black	0.0000238	0.0144***	-0.0258***
	(0.0000185)	(0.000909)	(0.000957)
Hispanic	-0.0000315*	0.0383***	-0.0314***
	(0.0000180)	(0.000881)	(0.000928)
Age	-0.000338***	0.0112***	-0.00268***
	(0.00000830)	(0.000408)	(0.000430)
Age-squared	0.00000610***	-0.0000452***	-0.0000883***
	(0.000000100)	(0.00000710)	(0.00000740)
Median Household Inc	-7.25E-10	0.0000001**	-0.0000003***
	(0)	(0)	(0)
Obesity	0.0000156	0.189***	-0.111***
	(0.0000425)	(0.00208)	(0.00220)
Diabetes	0.000424***	0.109***	-0.165***
	(0.0000794)	(0.00389)	(0.00410)
Hypertension	0.000774***	0.0802***	-0.0819***
	(0.0000800)	(0.00392)	(0.00413)
Asthma	-0.0000184	0.00921***	0.00228
	(0.0000409)	(0.00201)	(0.00211)
Hypothyroidism	-0.0000246	0.0264***	-0.0107***
	(0.0000585)	(0.00287)	(0.00302)
Cord Complications	-0.00000630	-0.0720***	0.116***
	(0.0000174)	(0.000852)	(0.000898)
Smoking	0.000441***	0.00168	-0.0265***
	(0.000109)	(0.00532)	(0.00561)
Length of Stay	0.000141***	0.0344***	-0.0240***
	(0.00000300)	(0.000147)	(0.000155)
Insurance Status			
Medicaid	0.00000900	-0.0202***	0.0260***
	(0.0000169)	(0.000830)	(0.000875)
Medicare	0.00104***	-0.0504***	-0.0303***
	(0.0000921)	(0.00452)	(0.00476)
TriCare/Federal Gov	0.0000687	-0.0523***	0.0211***
	(0.0000560)	(0.00275)	(0.00289)
Veterans Affairs	-0.0000660	-0.0593***	0.0704***
	(0.000230)	(0.0113)	(0.0119)

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Table 2 cont.

Other State/Local Gov	-0.0000266	-0.0824***	0.0843***
	(0.000126)	(0.00616)	(0.00649)
Self pay	0.000663*	-0.0819***	0.0481***
	(0.0000386)	(0.00189)	(0.00199)
Non-payment	-0.0000181	-0.0395***	0.0521***
	(0.0000855)	(0.00419)	(0.00442)
Kidcare	-0.00043	0.0306***	-0.0229*
	(0.000238)	(0.0117)	(0.0123)
Commercial Liability	-0.000147	-0.00826	-0.206***
	(0.000539)	(0.0264)	(0.0278)
Workers' Comp	-0.000291	-0.204***	-0.0971
	(0.00143)	(0.0700)	(0.0738)
Other	0.000242	-0.0388***	0.0161**
	(0.000153)	(0.00751)	(0.00791)

*Notes: All models also include year-quarter fixed effects. The omitted categories are white non-Hispanics, patients with no comorbidities, and commercial insurance. Standard errors reported in parentheses *** p<.01, ** p<.05, * p<.1*

6.2. Regression Results

Table 2 reports results from estimating equation [1], specifying the marginal impact of non- Hispanic Black race and Hispanic ethnicity on three outcomes of interest while controlling for patient characteristics including patient age, median household income, comorbidities, and insurance status. The coefficients of interest, those on non-Hispanic Black and Hispanic cohorts, serve as baseline estimations or the estimated disparities in mortality and treatment in the sample. The disparities between non-Hispanic white and non-Hispanic Black populations in both cesarean delivery and IOL are persistent through all controls and statistically significant to the 1% level. Black race increases the likelihood of cesarean delivery by 1.44 percentage point which is a 5.20% change from the rate of cesarean delivery of white patients. For IOL, Black race decreases the likelihood by 2.58 percentage point which is a 3.82% decrease from the rate of IOL for white patients. While not statistically significant in this sample, Black race increases the likelihood of maternal death by 0.0024 percentage points which equates to a 43.8% increase from the rate of maternal death among white patients.

For Hispanic populations, the likelihood of mortality decreases by 0.003 percentage points which is a 55.1% decrease from the non-Hispanic white cohort. Their likelihood of cesarean delivery is 3.83 percentage points higher which is an 13.8% increase from the non-Hispanic white rate. Hispanic ethnicity decreases IOL by 3.14 percentage points which is a 4.64% decrease from the non-Hispanic white rate of IOL. Across the sample, having Medicare coverage or being a self-payer increases the likelihood of mortality. Nearly all insurance coverage, in comparison to commercial insurance, decreases the likelihood of cesarean delivery, and most primary payers, except Medicare, increase the likelihood of IOL. This pattern could be observed due to the payment structure in the U.S. healthcare system where intrapartum payments vary by insurance coverage. One study found that in 2010, the average commercial intrapartum payment for cesarean births was nearly three times that of Medicaid intrapartum cesarean birth payments (Corry, 2013). It is also important to note that the Medicare births are rare because the only patients under the age of 65 on Medicare would be those with social security disability insurance coverage. The associations between comorbidities and the outcomes of interest show that most comorbidities increase the likelihood of mortality and cesarean delivery while they decrease the likelihood of IOL. Similarly, mortality outcomes seem to be worse for the youngest and oldest patients.

Table 3 attempts to delineate the between- and within-provider differences in maternal treatment and outcomes by race and ethnicity. For each outcome, I display the coefficient for non- Hispanic Black or Hispanic as I begin with baseline models and move onto models with more controls. There are three panels: results for maternal mortality (Panel I), cesarean delivery (Panel II), and IOL (Panel III). Within each panel, I display the raw differences between the non-Hispanic white cohort and either the non-Hispanic Black cohort or the Hispanic cohort (row a) as well as the results of estimating equations [1] through [4] (rows b-e). Table 3 reiterates the baseline estimations for all outcomes of interest and allows for their comparison to the effects of being Black or Hispanic on maternal mortality, cesarean delivery, and IOL when hospital fixed effects or physician fixed effects are

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absorbed within the model. The models including fixed effects also include the full set of controls as described by equations [2] and [3], but those coefficients are not reported for presentation and comparison purposes.

In comparing rows (a) and (b) in Panel I, observed patient characteristics explain most of the racial disparity in maternal mortality. Examining a pattern of results when hospital (row c) and physician fixed effects (row e) are added suggest that the non-random sort of patients into providers explains little of the disparity once individual controls are added (row b). The unexpected increase in the Black coefficient in absorbing hospital fixed effects is likely because Black patients go to hospitals with low rates of maternal mortality even if the racial cohort experiences differentially higher rates of mortality. By comparing Hispanic patients to non-Hispanic white patients in column (2) of Panel I, the modest benefit of being Hispanic on maternal mortality increases once observable patient characteristics are included in the model (row b). This suggests that even though Hispanic patients generally have worse observed patient characteristics than non-Hispanic white patients, they are less likely to die. Adding hospital fixed effects or controls for observable hospital characteristics does not alter the ethnic difference, but when physician fixed effects are absorbed, the negative coefficient is largely eliminated. This suggests that Hispanic patients visit physicians that have better than average outcomes in terms of maternal mortality as compared to the physicians that non-Hispanic white patients visit.

By comparing coefficients in Panel II, I estimate the effect of absorbing fixed effects on disparities in cesarean delivery. Rows (a) and (b) in both columns (1) and (2) demonstrate that with even with observed patient characteristic controls, Black and Hispanic patients are still more likely to experience cesarean delivery. When hospital fixed effects (row c) are absorbed, the positive coefficient that demonstrated a baseline racial disparity (row b) when controlling for observed patient characteristics is mostly eliminated. This suggests that the non-random sort of Black patients to hospitals explains a significant portion of the racial disparity in cesarean delivery. Because observed hospital characteristic controls do not reflect the same results as controlling for hospital fixed effects, it appears that unobservable hospital characteristics account for more of the racial disparity in cesarean delivery. Similarly, adding physician fixed effects (row e) eliminates the positive coefficient in column (2) of Panel II, suggesting that the non-random sort of patients to physicians explains a significant portion of the ethnic disparity in cesarean delivery. More specifically, the absorption of hospital fixed effects accounts for 89.1% of the initially reported racial disparity, and the absorption of physician fixed effects diminishes the marginal effect of being Hispanic by 99.8%.

For IOL, rows (a) and (b) in both columns (1) and (2) of Panel III demonstrate that even after controlling for observed patient characteristic controls, Black and Hispanic patients remain less likely to experience IOL than non-Hispanic white patients. By absorbing hospital fixed effects (row c), the racial disparity decreases 72.7% and the ethnic disparity decreases 93.3% to a less significant disparity. This suggests that, particularly for Hispanic patients, the non-random sorting of Black and Hispanic patients to hospitals explains a portion of the cohort's disparity in IOL. Similarly, the absorption of physician fixed effects (row e) decreases the racial disparity by 63.3% and the ethnic disparity by 85.8%. Although the non-random sorting of Black and Hispanic patients to physicians explains some part of the disparities in IOL, none of these fixed effect controls render the disparities insignificant from non-Hispanic white rates of IOL.

Across all panels, the estimates of equation [4] are displayed in row (d) where only observed hospital characteristics are used as hospital-level controls in place of hospital fixed effects. This evaluates to what extent such observable characteristics account for disparities in all three outcomes.

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Table 3. Linear Probability Model Estimations, With and Without Absorption of Hospital and Physician Fixed Effects

Population Cohort	(1) Non-Hispanic Black	(2) Hispanic
Panel I. Maternal Mortality		
(a) Raw Differences	0.0111***	-0.000839
	(0.00222)	(0.00136)
(b) Baseline model estimations	0.00238	-0.00315*
	(0.00185)	(0.00180)
(c) Absorbing hospital fixed effects	0.00288	-0.00286
	(0.00199)	(0.00204)
(d) Baseline with observed hospital characteristics	0.00287	-0.00244
	(0.00188)	(0.00183)
(e) Absorbing physician fixed effects	0.00442**	-0.000680
	(0.00183)	(0.00189)
Panel II. Cesarean Delivery		
(a) Raw Differences	1.00***	3.13***
	(0.0881)	(0.0890)
(b) Baseline model estimations	1.44***	3.83***
	(0.0909)	(0.0881)
(c) Absorbing hospital fixed effects	0.157*	0.409***
	(0.0949)	(0.0972)
(d) Baseline with observed hospital characteristics	1.02***	3.07***
	(0.0916)	(0.0894)
(e) Absorbing physician fixed effects	0.371***	0.00820
	(0.0960)	(0.0992)
Panel III. Induction of Labor		
(a) Raw Differences	-1.65***	-2.32***
	(0.0922)	(0.0921)
(b) Baseline model estimations	-2.58***	-3.14***
	(0.0957)	(0.0928)
(c) Absorbing hospital fixed effects	-0.704***	-0.210**
	(0.100)	(0.103)
(d) Baseline with observed hospital characteristics	-2.59***	-2.67***
	(0.0965)	(0.0942)
(e) Absorbing physician fixed effects	-0.946***	-0.447***
	(0.101)	(0.105)

*Notes: Raw Differences display the difference in outcomes rates between the minority sample and the white sample. All coefficients have been multiplied by 100 to report as percentage points. Standard errors reported in parentheses *** p<.01, ** p<.05, * p<.1*

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Table 4. Hospital Characteristics for Full Sample and by Population Cohort

Variable	Non-Hispanic White	Non-Hispanic Black	Hispanic	Full Sample
Bed Count	621.0	747.3***	764.4***	687.2
By urbanicity				
Urban	0.963	0.983***	0.979***	0.972
Rural	0.037	0.017***	0.021***	0.028
By ownership type				
Church Ownership	0.067	0.068	0.047***	0.062
Not for Profit	0.426	0.380***	0.483***	0.429
For Profit	0.224	0.219***	0.199***	0.216
Public	0.194	0.261***	0.206***	0.213
By Neonatal ICU				
No NICU	0.294	0.370***	0.427***	0.345
NICU Level I or II	0.427	0.300***	0.275***	0.359
NICU Level III	0.279	0.330***	0.298***	0.296
By volume of births in sample				
Low Volume	0.083	0.043***	0.050***	0.065
Medium Volume	0.295	0.249***	0.248***	0.272
High Volume	0.622	0.708***	0.701***	0.663
N	809,898	387,609	391,867	1,589,374

*Statistically significant differences in mean between NH Black and NH white or between Hispanic and NH white indicated by *** for .01, ** for 0.05, * for .10.*

In both cesarean delivery and IOL rates, these observed characteristics of hospitals decrease both the racial and ethnic disparities but to a lesser extent than the absorption of hospital fixed effects. Table 4 provides the descriptive statistics of observable hospital characteristics included in the estimation of equation [4]. All observable hospital characteristics are statistically significant in comparing the hospitals Black and Hispanic patients go to with those of non-Hispanic white patients, except for church ownership where Black and white patients are equally likely to find themselves treated. Black and Hispanic patients are more likely to go to more urban hospitals, hospitals with higher bed counts, public hospitals, hospitals lacking a NICU, and hospitals with higher volumes of births. Again, these observable hospital characteristics do not account for much of the racial and ethnic disparities even though there are significant differences in the hospitals the population cohorts are likely to go to.

Table 5 displays further analysis which ran equation [1] for all three outcomes of interest for three groups based upon the percent of patients on Medicaid in each hospital facility. In general, the percent of patients on Medicaid at a given facility can feasibly represent the socioeconomic status of the surrounding area. So, facilities with a low percentage of patients on Medicaid are likely to exist in areas of higher wealth. The results suggest that Black patients who go to facilities where either low or high percentages of patients are on Medicaid have better maternal mortality outcomes. For cesarean delivery rates, both Black and Hispanic patients do significantly better in terms of having lower rates of cesarean delivery in hospitals where more patients are on Medicaid. Hispanic patients have an extremely high increase in cesarean delivery in wealthier area facilities but have lower rates of cesarean delivery in hospitals where most patients are on Medicaid. IOL outcomes follow a similar pattern in that they are also worse for both Black and Hispanic patients in wealthier areas but are improved among facilities with a high percentage of patients on Medicaid.

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Table 5. Linear Probability Model Estimations by Medicaid Cohorts

Medicaid Cohort	Non-Hispanic Black	Hispanic
Panel I. Maternal Mortality		
Raw Differences	0.0111***	-0.000839
	(0.00222)	(0.00136)
Low Percent of Patients on Medicaid	0.00178	-0.00412*
	(0.00263)	(0.00230)
Medium Percent of Patients on Medicaid	0.00817***	0.00265
	(0.00267)	(0.00396)
High Percent of Patients on Medicaid	0.00390	-0.00680
	(0.00472)	(0.00468)
Panel II. Cesarean Delivery		
Raw Differences	1.00***	3.13***
	(0.0881)	(0.0809)
Low Percent of Patients on Medicaid	1.46***	7.58***
	(0.153)	(0.134)
Medium Percent of Patients on Medicaid	1.98***	1.32***
	(0.151)	(0.173)
High Percent of Patients on Medicaid	-0.453***	-0.640***
	(0.171)	(0.169)
Panel III. Induction of Labor		
Raw Differences	-1.65***	-2.32***
	(0.0922)	(0.0921)
Low Percent of Patients on Medicaid	-3.74***	-6.59***
	(0.160)	(0.140)
Medium Percent of Patients on Medicaid	-2.77***	-1.63***
	(0.159)	(0.182)
High Percent of Patients on Medicaid	0.305*	2.07***
	(0.183)	(0.182)

*Notes: Raw Differences display the difference in outcomes rates between the population cohort sample by race/ethnicity and the white population cohort sample. All coefficients have been multiplied by 100 to report as percentage points. Standard errors reported in parentheses *** p<.01, ** p<.05, * p<.1*

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6.3. Discussion and Conclusion

In this paper, I examine whether the non-random sorting of Black and Hispanic patients to hospitals and physicians can explain disparities in maternal care and outcomes. I find that hospital- level variation explains most of the racial disparity in cesarean delivery and some of both the racial and ethnic disparities in cesarean delivery and IOL. Physician-level variation, then, accounts for most of the ethnic disparity in cesarean delivery and some of both the racial and ethnic disparities in cesarean delivery and IOL. In terms of maternal mortality, much of the racial disparity remains unexplained by provider variation which suggests that the hospitals and physicians that treat Black patients are not directly causing disparities in maternal mortality within the sample. Because observed patient characteristics explain nearly all of the racial disparity in maternal mortality, even in a sample where health risk-related comorbidities are underrepresented, there may be inequities that lie beyond the scope of provider differences that contribute to racially disparate measures of maternal mortality.

These results suggest that the differences between hospitals and physicians which treat patients of different cohorts can explain a significant portion of the differential rate of maternal treatment for Black and Hispanic patients. Therefore, the way in which patients are matched to hospitals and physicians for treatment does, in fact, contribute to the racial and ethnic disparities in cesarean delivery and IOL. Despite decreases in disparate rates for these treatment outcomes with fixed effect absorption, differences between hospitals and between physicians persist for all outcomes of interest except for with hospital-level variation and the racial disparity in cesarean delivery as well as physician-level variation and the ethnic disparity in cesarean delivery.

The data used to construct these results present certain limitations to their validity. Because the available Florida inpatient dataset recorded by the Agency for Health Care Administration is administrative records that lack personally identifiable information, patients could not be matched to entire medical histories which might detail comorbidities not reported in the sample hospitalizations. The rates of all comorbidities are incredibly low and do not parallel much of the rates found in the U.S. population which suggests that underreporting of health risk factors is a significant problem in Florida hospital records for births.

Similarly, observations could not be matched to specific individual characteristics beyond what the administrative hospital records report. This means that the socioeconomic status indicator used, median household income within the patient's recorded zip code of residence, may not accurately represent the true socioeconomic status of patients. There were many observations missing median household income due to missing data in patient zip code, including those of any patients born outside the U.S., which is particularly important in a setting like Florida where immigrant populations that may identify as Black or Hispanic are likely to be large. As the income-health association is widely confirmed, there may be impacts of socioeconomic status on all outcomes of interest for which the models fail to control. Further, maternal death is generally defined to be death during pregnancy or within 42 days of the end of the pregnancy ("Maternal Deaths"). Because the sample observations cannot be matched to other hospitalizations, I do not account for any maternal deaths that occur prior to the childbirth hospitalization or following that initial hospitalization.

The results of the models controlling for physician fixed effects are threatened by the nonuniformity of risk within the occurrence of childbirth. Since some physicians who are specialists may tend to see higher risk patients–which is more likely for Black or Hispanic patients–they would be linked to higher rates of mortality and cesarean delivery. The models attempt to control for this by using length of stay as a patient characteristic control. Patients who experience complications, especially in a cesarean delivery, will remain in the hospital longer, but this may not control for all instances of birth complication.

Because my focus lies in the Black-white and Hispanic-non-Hispanic disparities, these results do not apply to other racial disparities that exist in maternal mortality and cesarean delivery occurrence. This prompts further study to determine how hospital and physician variation contribute to racial and ethnic disparities which may disadvantage Asian, Native American and Alaskan Native, and Native Hawaiian or Pacific Islander social groups.

My findings point toward the need for interventions at both the hospital and physician level to improve maternal treatment and outcomes for Black and Hispanic patients. Because hospital variation contributes to a significant portion of the racial disparity in cesarean delivery and of the ethnic disparity in IOL, improvements in resource quality and access aimed at promoting vaginal birth with IOL when it is medically favorable could be directed toward facilities which tend to treat Black and Hispanic patients. Additionally, medical facilities might have an opportunity to establish hospital-wide policies limiting the use of the racialized VBAC algorithm in favor of unbiased methods. Since observed hospital characteristics did not explain disparities to the same extent that the absorption of hospital fixed effects did, it is likely that unobserved hospital characteristics are more responsible for racial and ethnic disparities in health. This means that less measurable elements like staff quality, management styles,

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institution ethos, and practice patterns may play a larger role in emergent health disparities. These elements are difficult to measure, but they are not unchangeable. Efforts to alter unobserved characteristics will require more intentioned efforts to target facility-wide culture and practices. Further, in the supplemental analysis using percent of patients on Medicaid as a proxy for the wealth of a facility's surrounding area, treatment outcomes are significantly worse for minority patients in wealthier areas. Therefore, it is necessary to pursue a more equitable distribution of funding and resources not only between facilities which serve different social cohorts but also between social cohorts at a given facility.

Similarly, since physician variation explains nearly all the ethnic disparity in cesarean delivery, a portion of the racial disparity in cesarean delivery, and a portion both disparities in IOL, there needs to be further examination into how these disparities manifest across physicians. Policymakers, medical facilities, and physicians themselves can minimize the variation between physicians in their treatment of maternal health. Specifically, policymakers might reevaluate the ways in which physicians are compensated for certain procedures to better direct their decision-making in maternal treatment. Facilities might implement programs which seek to minimize implicit biases within their physicians. My results not only establish that racial and ethnic disparities persist in maternal death, cesarean delivery, and IOL and prompt further investigation of the emergence of these disparities but also suggest the existence of possible solutions toward equity in decreasing the effects of institutionalized racism within the U.S. healthcare system.

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Article

Demand for Informal goods in Africa: Demand System Estimation with Quality Effects and its Limitations

Kexin Wu[1]

[1] Student (BSc Economics, 2020-23), University College London, United Kingdom;
kexin.wu.20@ucl.ac.uk

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Abstract

The growth of many African Economies is accompanied by an unusual expansion of the informal sector but the demand for informal goods is rarely tested. This study examines the demand for informal goods in Africa, specifically in the Democratic Republic of the Congo in 2012, using household-level survey data. This paper reviews and summarizes that income inequality, quality preference, and preference for some product-specific characteristics are the main drivers of the demand for informal goods. This paper hypothesizes three channels of demand for informal goods and uses the empirical method in Angus Deaton (2018) to test the hypothesis by estimating expenditure elasticity, price elasticity, and quality elasticity. The results show that the demand for informal goods generally decreases as income increases and income inequality reduces, but this pattern can differ for different categories of goods. The results show that the three channels are likely to be plausible and informal and formal goods can be both substitutes or complements in the final markets. Policies to improve formality may consider the different demand patterns across markets to be more effective. Potential limitations of the method in this specific context and implications for future improvements are discussed.

Keywords: Demand Estimation, Quality effect, Informal Sector

1. Introduction

Since 2000, the gradual take-off of total employment and economic growth in many African countries like Ethiopia, Ghana, and Kenya is largely contributed by the expansion of informal employment, with formal employment remaining relatively stagnant (McMillan and Zeufack, 2022; Diao et al., 2021). Medina, Jonelis, and Cangul (2017) estimate that the size of the informal sector in Africa remained the highest in the world from 2010 to 2014 and varied from around 25 per cent in Mauritius and Namibia to over 40 per cent in the Democratic Republic of the Congo, Benin, and Nigeria. This is contradictory to patterns of Asian developing countries, such as Vietnam, where the take-off of total employment was accompanied by flat or even declining informal employment (McCaig and Pavcnik, 2018).

Most studies about expanding informal sectors in Africa focus on the supply side, like capital or labour costs. However, Diao et al. (2021) suggest that a supply-driven structural change should coincide with the expansion of formal activities in the manufacturing sector, while a demand-driven structural change is more likely to be observed with the marginal entrance of informal firms in Africa. Kruse et al. (2022) suggest that industrialization in Sub-Saharan Africa is accompanied by proliferating unregistered firms because there is a significant demand for informal manufactured goods. Few studies provide evidence about why there is substantial demand for informal goods and how the demand-side factors can relate to supply-side factors. If we ignore demand-side factors, we may fail to understand the full potential impact of policies to improve formality. Banerji and Jain (2007) suggest that some policies to improve formality from the supply side, like lowering the capital costs for informal firms, may help informal firms produce a wider range of products, compete with the formal sector, and promote informality. To understand the welfare implication of the expanding demand for informal goods, it is important to understand the demand pattern of informal goods in more detail.

This paper explores the demand for informal goods from three aspects. First, previous studies suggest that income inequality and consumers' preference for quality are necessary conditions for demand for informal goods in the final goods markets (Mishra and Ray, 2010; Mishra, 2022). There is also evidence about consumers choosing informal goods for other features like accessibility. This paper reviews interactions between income, preference for quality, and preference for other characteristics in determining the demand for informal goods, and summarizes three channels of the demand: First, informal goods are preferred only as cheaper and low-quality substitutes to formal goods; Second, informal goods are cheaper substitutes but are also preferred by their own traits except for the lower price; Third, informal goods are complements for formal goods.

Next, this paper uses the household-level expenditure data from the Democratic Republic of the Congo in 2012 and the aggregate demand system with quality effects from Deaton (2018) to estimate the demand for informal goods, providing estimates for income, price, quality elasticity and cross-price elasticity between informal and formal goods. The results show that the three channels summarized are likely to be plausible. The budget share for informal goods generally decreases as total expenditure increases, but this pattern can vary across categories of goods. For example, the budget share of informal transportation is increasing with income. Informal and formal goods can be imperfect substitutes or complements in the final markets. Thus, policymakers may customize policies in different markets to be more efficient.

Finally, since the demand for informal goods is rarely tested empirically and the method in this paper is applied under assumptions, this paper discusses the limitations in estimation and how future works may improve upon it.

The paper is organized as follows: Section II reviews evidence about the demand for informal goods in Africa. Section III hypothesizes the three channels of demand for informal goods. Sections IV and V introduce the dataset and the empirical strategy respectively. Section VI discusses the potential limitations of the method in the specific context and adjustments to data. Section VII discusses the empirical results.

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2. Literature Review

2.1. Disparity in Costs and Quality of Products between Formal and Informal Sectors in Africa

The informality of firms is generally defined by small size, lack of registration with government agents, lack of financial statements, and constrained access to credit (Benjamin and Mbaye, 2012). Constraints in production like high entry costs and financial constraints to accessing capital are exacerbated by constraints on the institution side like the weak legal framework (Dabla-Norris, Gradstein and Inchauste, 2008; Ulyssea, 2010).

Barriers between formal and informal sectors lead to a disparity in production, especially the lower capital-labour ratio in the informal sector (de Paula and Scheinkman, 2007). The informal sector in Africa is much more labour-intensive than the formal sector and is the main source of absorbing employment, especially among disadvantaged groups (Etim and Daramola, 2020). The wage of informal workers is on average lower due to the lower observable or unobservable skills and the lack of minimum wage enforcement (Bargain and Kwenda, 2014; Rauch, 1991). While the formal sector in Africa is not absorbing employment effectively, facing much higher labour costs relative to their productivity and better access to capital, making them more capital-intensive relative to their income level (Hernando De Soto, 2006; McMillan and Zeufack, 2022; Diao et al., 2021).

One implication of the disparity is the difference in the quality of products. Producing high-quality products requires more capital or high-skilled labour, and the costs of quality function are decreasing in the capital-labour ratio (Copeland and Kotwal, 1996). Thus, formal firms have advantages in producing high-quality goods, while informal firms have advantages in producing low-quality but cheaper counterparts. Consumers' choices depend on their preferences for quality and income (Banerji and Jain, 2007). The disparity in inputs can also lead to horizontal differentiation. The higher labour intensity of informal sectors allows their products to be more personalized, cultural, and traditional, while products from the formal sector are generalized and industrialized. In a market with both sectors, consumers' choices can depend on their preference for product-specific characteristics.

2.2 Empirical Evidence about Consumer Bases for Informal Goods in Africa

Empirical evidence about the demand for informal goods is quite rare in Africa. Böhme and Thiele (2012) apply household-level survey data from six African countries to show that households working in both the informal and formal sectors have a significant demand for informal goods. Besides, the income elasticity of informal goods is consistently less than one across countries. Their results suggest that the expenditure share on informal goods is decreasing in income though there are overlapping consumer bases between informal and formal goods. These estimates classify most foods and non-alcoholic beverages as informal goods while classifying electricity, fuel, clothing, and footwear as formal goods. The estimates aggregate across categories of goods, and the heterogeneity between categories was untested due to data limitations. Bachas, Gadenne, and Jensen (2020) define formality based on the probability that the consumption taxes are included in the consumer prices in a particular distribution channel. The informal Engel curve (IEC) is on average flatter and higher for African countries like the Democratic Republic of the Congo. This result implies budget shares for informal goods are decreasing but persistent across income groups.

2.3. Important Building Blocks for the Demand for Informal Goods

The first factor to explain the demand for informal goods is income inequality. As discussed in Section II.1, due to the cost dualism, formal and informal sectors have advantages in producing goods of different quality. The mechanism through which income inequality affects the demand for informal goods is closely related to people's preference for quality. Mishra and Ray (2010) develop a model specifying informal and formal goods as close substitutes, showing that a sufficiently high inequality of income is necessary to generate demand for low-quality informal products. The persistent demand for informal goods is mainly because income inequality is too high and the demand for informal goods is decreasing with income. Mishra (2022) shows that the coexistence of the informal and formal sectors is less likely to reach equilibrium if consumers' preference for high-quality formal goods over low-quality informal goods is not large enough.

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Banerji and Jain (2007) model the disparity on the supply side between informal and formal sectors and propose that this would lead to the quality dualism between informal and formal goods at equilibrium. At the equilibrium, high-quality formal goods are chosen by consumers with incomes higher than a certain threshold, while low-quality informal goods are chosen by consumers with incomes lower than the threshold.

Böhme and Thiele (2012) suggest that if there is a significant quality dualism, we should observe a lower income elasticity for informal goods, which is consistent with their estimation of elasticity in African countries. Nearly half of the subcategories exhibit significant differences in unit prices between informal and formal goods, and 96 per cent of them show a lower value for informal goods. Bachas, Gadenne, and Jensen (2020) show that in the Democratic Republic of the Congo, 34.4 per cent of the purchases of informal goods are explained by their lower prices. However, except for prices and quality, half of the purchases of informal goods are for other reasons, like access or store attributes, affecting people's preference for quality. Preference for some product characteristics may interact with quality preference and income. Besides, models generally assume that informal and formal goods are imperfect substitutes while ignoring the possibility that they can be complements in some markets.

3. Hypothesis: Three Channels of Demand for Informal Goods

First, informal goods are preferred by low-income households as cheaper and low-quality substitutes for formal goods. The demand for informal goods is mainly attributed to income inequality and consumers' preference for quality. The budget share on informal goods decreases as income increases. The expenditure elasticity for informal goods is expected to be less than one and lower than that of formal goods.

Second, informal goods are imperfect substitutes for formal goods but are appreciated by a wider range of households for some other characteristics, which can give them more power to compete with formal goods as consumers' income increases. We may expect the income elasticity of informal and formal goods to be similar or even higher for informal goods.

Third, informal goods can be complementary goods to formal goods. Tucho (2022) suggests that in many Sub-Saharan cities, informal non-motorized transportation is complementary to formal motorized transportation. As the country develops, imported or industrialized goods begin to appear in the market, but it can take time for consumers to fully accept them, and consumers may still need informal goods to complement their formal purchases.

4. Data

The data used in this paper is from the National Household Survey of the Democratic Republic of the Congo (DRC) in 2012 by the National Institute of Statistics, covering 21454 households (National Institute of Statistics, 2012). This is a standardized 1-2-3 survey. Phase 1 is a general employment survey, providing detailed sociodemographic characteristics of households and employment. Phase 2 targets heads of informal production units, investigating their economic performance. Phase 3 is an expenditure survey, including aggregate data on the total expenditure of 12 categories of goods. Households are identified by the site number (national identification number for all districts and villages from 1 to n) and the number of households (coding households in one site).

The most important dataset for this study is module 11 of phase 3, which recorded households' daily expenditure on final goods within 15 days of the survey. Households can have more than one record of the purchase in module 11. Module 11 is a representative sample of 15005 households of the phase 1 sample. The classification of goods follows the COICOP12 nomenclature. Module 11 includes 9 categories of goods only, excluding education expenditure, hotel or restaurant expenditure, and miscellaneous goods and services. Data from module 11 is matched with demographic variables in phase 1. The summary statistic for the main demographic variables is shown in Table 1.

Table 2 below shows the share of expenditure of 12 categories of goods in phase 3 according to the quintile of total expenditure. If we classify informal and formal goods by categories as in Böhme and Thiele (2012), then the expenditure on informal goods like food and non-alcoholic beverages is decreasing in income, while formal goods like communication and transportation are increasing in income. The second way of classifying informal goods is by the distribution channel (Bachas, Gadenne, and Jensen,

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2020). Since this paper explores the demand pattern for informal goods both in general and for decomposed categories, and substitutability is one of the main interests, classifying informal and formal goods by categories is not justified. Thus, this paper classifies informal and formal goods by distribution channels, using the indicator in module 11 shown in Table 3. Besides, to eliminate the possible subcontracting of formal goods to informal distribution channels, I adjust the channel indicator by classifying industrialized, imported goods, and consumption involving the usage of public infrastructures as formal goods. The full adjustment by product codes is included in Appendix 1.

Table 1: Summary Statistics for Selected Demographic Variables in Phase I

	Mean	Sd	Observations	Min	Max
Site	3504.126	2144.081	15005	10	7020
Menage	12.20187	8.445378	15005	1	40
Total Expenditure(in Congolese Franc)	1915017	4959132	15005	8200	5.48e+08
Number of Adults	4.262338	2.208481	15005	.72	17.88
Household Size	5.282706	2.73136	15005	1	22
Number of Members Aged Above 5	4.308697	2.37705	15005	1	18
Province	5.286638	3.154936	15005	1	11
Age (Head)	44.2217	14.24288	14989	15	98
Sex (Head) (1=Male)	.8125958	.3902487	15005	0	1
Years of Study (Head)	8.099571	5.001173	14462	0	21
Working Sector (Head)(1=formal)	.2095968	.4070344	15005	0	1
No Education (=1)	.1568144	.3636378	15005	0	1
Primary Education (=1)	.2069977	.4051673	15005	0	1
No formal Education (=1)	.006931	.0829665	15005	0	1
Secondary Education (=1)	.4893036	.4999022	15005	0	1
High Education (=1)	.1133622	.3170456	15005	0	1
Vocational Education (=1)	.0097967	.0984957	15005	0	1

Note: Only the sample of 15005 households is included here. Variables included in this table are used as control variables in later regression or used to generate control variables for later regressions. HSECTOR indicates the working sector of the household head, which equals 0 if the household head is working in the agricultural or non-agricultural informal sector, unemployed, retired, or inactive, and equals 1 if the head is working in the public sector or formal private sector. Details for generating other variables are shown in the do files provided. Total expenditure in this table includes the total household expenditure of 12 categories recorded in phase 3, including expenditure in memory and non-daily expenditure like education and hotel. Column Sd means standard deviation.

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Table 2: Average Budget Shares by Categories

	(1) First Quartile mean	(2) Second Quartile mean	(3) Third Quartile mean	(4) Fourth Quartile mean
1 Food/Non-alcoholic Beverages	.7443695	.7240466	.6870451	.597793
2 Alcoholic Beverages	.0185005	.0154278	.0152805	.017297
3 Clothing	.0205116	.024333	.0277453	.0307259
4 Housing	.1345526	.138374	.1606838	.1857187
5 Furnishing	.030115	.0296118	.0280484	.0342221
6 Health	.0121706	.0156174	.0145719	.0151105
7 Transportation	.004885	.0091243	.015843	.0356724
8 Communication	.002439	.0057898	.0090357	.0191471
9 Leisure	.0049803	.0054028	.0055001	.0085978
10 Education	.0092385	.0099588	.0119747	.018898
11 Hotel/Restaurant	.0033694	.0053112	.0066497	.0151312
12 Miscellaneous Goods/Services	.0148681	.0170025	.0176218	.0216863
Observations	3298	3772	3859	4076

Note: The quartile of total expenditure is classified using the variable QUART in phase 3. Details of codes and labels are available in the do files provided.

Table 3: Labels of the Channel Indicator in Module 11

Informal	Formal
01 Gift Given	07 Purchase in Supermarket
02 Gift Received	08 Purchase in a formal shop or Workshop(Company)
03 Self-produced Goods/Services	09 Purchase from the Public or Semi-public Sector
04 Purchase at Sellers' Home/ Small Shops/Informal Workshops	10 Other Formal Purchasing Place
05 Purchase on Public Markets	11 Purchasing Abroad
06 Other Informal/Independent Shops	

Note: The channel indicator is given in the original data of module 11. Details are available in the codebook and do files.

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5. Empirical Strategy

5.1 Quality, Price, and Unit Values

In practice, the most prevalent measure of quality for a group of goods is the unit value, which is the ratio of expenditure on a group of goods and the quantity purchased. In the household survey, price data is hard to collect, and there is a variation of price across villages which is particularly pervasive in most African countries, where markets are not integrated due to underdeveloped transportation (Deaton, 1987). The data of unit value is easier to obtain but cannot be a perfect substitute for price because it contains the effect of both price and quality. Unit values can be seen as the proxy for quality and price, but if we want to estimate price elasticity matrices and expenditure elasticity, it is crucial to rule out the quality effect and control for the variation across clusters.

The empirical method and codes are from Deaton (2018). The following sections show how this method can help separate the quality effect and recover price elasticities, control for regional variation of prices, and alleviate measurement error, simultaneity bias, and data limitation.

5.2. Modelling of Quality

According to Deaton (2018), the relationship between quality, quantity and price is defined as follows.
For a group of good G, the group quantity index QG is expressed by the household's vector of consumption levels of each item within the group, qG, and adjusted incommensurate items by kG,

$$Q_G = \boldsymbol{k_G q_G} \quad (1)$$

The corresponding unobserved price vector p_G is,

$$\boldsymbol{p_G} = \pi_G \boldsymbol{p_G^0} \quad (2)$$

where p_G^0 is the reference price vector which is constant across clusters. π_G is a scalar measuring the level of prices within group G, varying across clusters. The expenditure on group G is,

$$x_G = \boldsymbol{p_G q_G} = Q_G \pi_G \left(\frac{\boldsymbol{p_G^0 q_G}}{\boldsymbol{k_G q_G}}\right) \quad (3)$$

The quality ξ is the expenditure of a bundle at p_G^0 relative to the physical volume Q_G,

$$\xi_G = \frac{\boldsymbol{p_G^0 q_G}}{\boldsymbol{k_G q_G}} \quad (4)$$

Thus,

$$x_G = Q_G \pi_G \xi_G \quad (5)$$

and,

$$\ln(x_G) = \ln(Q_G) + \ln(\pi_G) + \ln(\xi_G) \quad (6)$$

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The unit value v_G is defined as the ratio of the expenditure of the goods and the physical quantity,

$$v_G = \frac{x_G}{Q_G} = \frac{\boldsymbol{p_G q_G}}{Q_G} = \xi_G \pi_G \quad (7)$$

Assuming separable utility across groups and subgroup demand functions are homogeneous of degree zero,

$$\boldsymbol{q_G} = f_G(x_G, \boldsymbol{p_G}) = f_G\left(\frac{x_G}{\pi_G}, \boldsymbol{p_G^0}\right) \quad (8)$$

Thus, the quality ξ_G depends on price π_G only through q_G, which in turn depends on the ratio x_G/π_G, by chain rule and rearrangements,

$$\frac{\partial ln\xi_G}{\partial ln\pi_G} = \frac{\partial ln\xi_G}{\partial lnx_G}\left[\frac{\partial lnx_G}{\partial ln\pi_G} - 1\right] \quad (9)$$

The last term in (9) in the bracket is the price elasticity of Q_G with respect to π_G, denoted by ϵ_P.

Specify the basic clustered aggregate demand model for one good,

$$w_{Ghc} = \alpha^0 + \beta^0 lnx_{hc} + \gamma^0 z_{hc} + \theta ln\pi_{Ghc} + f_{Gc} + u_{Ghc}^0 \quad (10)$$

$$lnv_{Ghc} = \alpha^1 + \beta^1 lnx_{hc} + \gamma^1 z_{hc} + \psi ln\pi_{Ghc} + u_{Ghc}^1 \quad (11)$$

where w_{Ghc} and v_{Ghc} are the budget share and unit values of goods for household *h* in cluster *c* respectively. x_{hc} is the total expenditure for the household, π_{Ghc} is the unobserved price faced by the household and f_{Gc} is the cluster fixed effect. The assumption is that market prices vary across clusters but do not vary within them over the survey period. z_{hc} includes other demographic variables.

By (7), given π_G is the scalar vector on a cluster level, which is independent of the household's total income *x*, ignoring the household identifier subscript of *hc* for simplicity,

$$\frac{\partial lnv_G}{\partial lnx} = \frac{\partial ln\xi_G}{\partial lnx} + \frac{\partial ln\pi_G}{\partial lnx} = \frac{\partial ln\xi_G}{\partial lnx} \quad (12)$$

Then by (11) and (12), we can get the Prais-Houthakker income elasticity of quality, β^1 (Prais and Houthakker, 1971),

$$\beta^1 = \frac{\partial lnv_G}{\partial lnx} = \frac{\partial ln\xi_G}{\partial lnx} = \frac{\partial ln\xi_G}{\partial lnx_G}\frac{\partial lnx_G}{\partial lnx} \quad (13)$$

which identifies the relationship between income and quality. Intuitively, they should be positive since people are more willing to pay for quality as their income increases.

The last term in (13) is the expenditure elasticity of group G, ϵ_x, so we can express the first term in (13) by β^1 and ϵ_x and then substitute back to (9), and by (11), we can get the relationship between quality, price, and expenditure elasticity,

$$\psi = \frac{\partial lnv_G}{\partial ln\pi_G} = \frac{\partial ln\xi_G}{\partial ln\pi_G} + 1 = \frac{\beta^1 \epsilon_p}{\epsilon_x} + 1 \quad (14)$$

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By (10), the budget share elasticity with respect to x is β^0/w, which includes both the quality and quantity effect of income. By the definition of the budget share, (4), (6) and (12),

$$\frac{\beta^0}{w_G} = \frac{\partial lnw_G}{\partial lnx} = \frac{\partial \ln\,(v_G Q_G/x)}{\partial lnx} = \beta^1 + \epsilon_x - 1 \quad (15)$$

Then similarly, by (11) and (14), and the definition of price elasticity ϵ_p,

$$\epsilon_p + \psi = \frac{\theta}{w_G} = \frac{\partial lnw_G}{\partial ln\pi} = \frac{\partial \ln\,(v_G Q_G/x)}{\partial ln\pi} \quad (16)$$

Then by (14), and by substituting (15) and (16) in,

$$\psi = 1 - \frac{\beta^1(w_G - \theta)}{\beta^0 + w_G} \quad (17)$$

Suppose $\phi = \theta/\psi$, which can be estimated. Given that θ can be recovered by,

$$\theta = \frac{\phi}{1 + (w_G - \phi)\zeta} \quad (18)$$

In which,

$$\zeta = \frac{\beta^1}{\beta^0 + w_G(1 - \beta^1)} \quad (19)$$

After parameters in (17)-(19) are estimated, we can recover the elasticity in (15) and (16).

5.3 Two Stages Estimation

The method below from Deaton (2018) is slightly adapted to use budget share and add demographic factors.

There are two stages; in the first stage, we run the regressions (10) and (11) without the price data and then construct the two variables below, ignoring the subscript of G for simplicity,

$$\hat{y}^0{}_{hc} = lnw_{hc} - \hat{\beta}^0 lnx_{hc} - \hat{\gamma}^0 z_{hc} \quad (20)$$

$$\hat{y}^1{}_{hc} = lnv_{hc} - \hat{\beta}^1 lnx_{hc} - \hat{\gamma}^1 z_{hc} \quad (21)$$

In (20) and (21), the effect of expenditure is filtered out while the cluster fixed effect and price effect are kept. We can get estimates for the variance of u^1_{hc} and covariance of u^1_{hc} and u^0_{hc}, denoted by $\hat{\sigma}^{11}$ and $\hat{\sigma}^{01}$.

In the second stage, we use cluster-level information and the subscript c only, the true average values y_c^0 and y_c^1 can be expressed as

$$y_c^0 = \alpha^0 + \theta ln\pi_c + f_c + u_c^0 \quad (22)$$

$$y_c^1 = \alpha^1 + \psi ln\pi_c + u_c^1 \quad (23)$$

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Then,

$$cov(y_c^0, y_c^1) = \theta\psi m + \frac{\sigma^{01}}{n_c} \quad (24)$$

$$var(y_c^1) = \psi^2 m + \frac{\sigma^{11}}{n_c} \quad (25)$$

where m is the variance of log prices in a large sample and n_c is the number of households per cluster.
Given (22)-(25), the estimate for ϕ is denoted by,

$$\hat{\phi} = \frac{cov(\hat{y}_c^0, \hat{y}_c^1) - \frac{\hat{\sigma}^{01}}{n_c}}{var(\hat{y}_c^1) - \frac{\widehat{\sigma^{11}}}{n_c}} \quad (26)$$

Then, substituting this back to (18), we can recover θ and obtain ψ from (17). Finally, substituting them back to (16), we can get estimates of price elasticities.

5.4. Final Regressions

The theoretical basis for the multi-good utility model with quality effects is that the consumer maximizes the sub-utility group subject to the amount spent on each group, assuming the overall utility function is separable in every group. The main stages of the estimation follow the same steps in the last sections, but the estimated parameters and price elasticity are matrices. The smallest unit of groups, the variable SITE in Table 1 is used as clusters.

Our final aggregate demand system for M groups of goods is,

$$w_{Ghc} = \alpha_G^0 + \beta_G^0 lnx_{hc} + \gamma_G^0 z_{hc} + \sum_{H=1}^{M} \theta_{GH} ln\pi_{Hc} + f_{Gc} + u_{Ghc}^0 \quad (27)$$

$$lnv_{Ghc} = \alpha_G^1 + \beta_G^1 lnx_{hc} + \gamma_G^1 z_{hc} + \sum_{H=1}^{M} \psi_{GH} ln\pi_{Hc} + u_{Ghc}^1 \quad (28)$$

The description of variables is shown in Table 4. Demographic variables z_{hc} includes household sizes, sex, age, years of schooling, and working sector of household heads, which are controlled to alleviate the potential correlated heterogeneity between total expenditure and budget shares or unit values. The fixed effect of provinces is removed in the estimation and the demand system is estimated for the full sample of module 11 and decomposed categories. Details are shown in Table 5.

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Table 4: Description of Variables in Regressions

Variable	Description
w_{Ghc}	Budget share of group G for household h in cluster c
lnv_{Ghc}	Unit values of group G for household h in cluster c in natural logarithm
lnx_{hc}	Total expenditure of household h in cluster c in natural logarithm
$lhhs_{hc}$	Household size of household h in cluster c in natural logarithm
SEXHEAD	Sex of the household head: Males=1, Female=0
YEAR_STUDY	Years of the household head in school or vocational training
HSECTOR	Working sector of the household head
AGEHEAD	Age of the household head
Province	Province of the household, labeled from 1 to 11

Note: The summary statistics of all demographic variables can be found in Table 1. The summary statistics for budget share and unit values are not provided here because their statistics vary across different categories. $lhhs$ is the natural logarithm of the variable 'Household Size' in table 1. lnx_{hc} is the natural logarithm of the total expenditure in table 1.

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Table 5: Description of Groups of Goods for Estimations

	Product Code	Description
A	All	Full sample of module 11 using adjusted product codes
B	11***	All foods
C	111**	Cereals, pastas, staples
D	112**, 113**	Meat, seafood
E	114**, 115**, 118**, 119**	Diary products, fat, sugar, sauce
F	116**, 117**	Fruit, vegetable
G	12***	Non-alcoholic beverage
H	2****	Alcoholic beverage
I	3****	Clothing
J	4****, 5****s	Furnishing, housing/decoration
K	6****	Health
L	7****	Transportation
M	9****	Communication (postal/telephone), leisure
N	All	Full sample using the original product code

Note: The channel indicator is given in the original data of module 11. Details are available in the codebook and do files. The adjusted channel indicator is used for all estimations, except N. The description of the adjusted channel indicator is available in section V and Appendix 1. Product codes provided gave 5 digits. The first digit from the left-hand side represents the category indicated in table 1. For example, 2**** in this table corresponds to 2 in table 1 and indicates alcoholic beverages. The second and third digit indicates narrower categories. For example, 11*** means food only and 111** indicates cereals, pasta, and staples only.

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6. Limitations and Further Adjustment of Data

6.1. Unit Values, Services, and Groups of Goods for Regressions

First, unit values are considered a better proxy for prices of foods than other categories of goods. To alleviate the measurement error in the calculation of unit values, I remove records of nonquantifiable services in module 11 because the definition of physical quantity for services is vague. The code and descriptions for services are available in Appendix 1. Besides, in Table 3, the informal channels recorded in module 11 include gifts given and gifts received, and to alleviate measurement errors, records from these two channels are removed.

Second, in household survey data, zero purchases of certain groups of goods are common. If both zero and non-zero purchases are included, then the method can be thought of as a linear approximation averaging over zero and non-zero purchases. However, in this study, we include non-zero purchases only because the data on the unit value of zero purchases is omitted. In this case, the results are estimated conditional on non-zero purchases. Thus, here we are interested in why households buy more or less of goods rather than why make a purchase, assuming that the purchases are randomly distributed with time. Using the median of unit values and budget shares for the missing records is usually a way to alleviate the problem of zero purchases. I impute the median values conditional on the demographic variables shown in Table 4, assuming that the recording is missing randomly conditional on those variables. This assumption is untestable. Both estimates with imputation and without imputation are provided and compared, but the results without imputation are the key to the discussion.

Besides, the functional form of the budget share regression assumes a linear Engel curve, but it can be quadratic. Furthermore, Gibson and Kim (2019) suggest that this method still underestimates the quality effect and overestimates the price elasticity of quantity. To further alleviate the simultaneity and measurement errors, instrumental variables for the expenditure terms can be considered. A comparison of existing empirical strategies for the demand systems is shown in Appendix 2.

6.2. Symmetry Restriction, Completing the System, and Statistical Inference

First, in survey data, given zero purchases and limited time of collection, there can be hundreds of different purchase combinations of goods, thus empirical specification cannot fully comply with the theoretical restriction of symmetry. Nonetheless, Deaton (2018) proposed a method to approach the symmetry constraint. Assuming that the quality effects are small, there is a way to obtain a price elasticity matrix that is symmetric in signs.

Second, we can hardly obtain full consumption lists of consumers. Deaton (2018) suggests that the adding-up and homogeneity restriction of the demand system allows us to add a fictitious good to complete the system. If we want to focus on several groups of goods only, all other goods are included in the fictitious good.

The expenditure elasticity should be interpreted cautiously because the method provides no standard error for it, but if estimates for β^0 or β^1 are not significant, it is hardly possible that the estimate for expenditure elasticity is significant. In the second stage, the standard errors for price elasticity matrices are obtained by bootstrapping, making 1000 draws from the clusters in the second stage, which is defined as half of the interval that contains 68.3 per cent of the bootstrapped estimates. The estimate for price elasticity is regarded as significant if it is larger than twice the bootstrapped standard error.

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7. Results

7.1. Empirical Results

This section discusses the result of groups A, C to H, I, and L in Table 5. Other results are shown in Appendix 3.

A: Full Sample

First, full sample results can give insight into the general linkage between informal and formal goods in the final product market. Table 6 shows the first-stage regression results with total expenditure elasticity, ϵx, and quality elasticity of income, $\beta 1$, for the estimation without and with the imputation of missing values.

According to equation (15), the positive quality elasticity of income is filtered out from the budget share elasticity, so the expenditure elasticity can be lower than estimates without considering the quality effects. The coefficient of lnx in both estimations is positive for formal goods while negative for informal goods, suggesting that the consumers would spend less budget on informal goods as total expenditure increases while more budget on formal goods. In Appendix 4, the linear Engel curves are estimated using the first-stage results. Ignoring quality effects, if the coefficient lnx is positive, we may expect that the expenditure elasticity is above the unity and the quantity demanded is also increasing in income, but the expenditure elasticity for formal and informal goods are all less than unity. The reason behind this is that the positive and significant quality effects of income, $\beta 1$, are filtered out. The quality elasticity, $\beta 1$, of income is positive for both informal and formal goods and higher for formal goods, implying that the quality of goods purchased increases as their total expenditure increases and the pace is quicker for the formal goods.

Another interesting coefficient to look at is that of the household size, lhhs. The coefficient of lhhs is negative for formal goods but positive for informal ones, suggesting that ceteris paribus on average, households with larger size is more likely to choose informal goods.

Table 7 shows the estimations of price elasticity. Since the quality elasticity is significant, as discussed in section VI.2, it is better to look at the unconstrained estimates of price elasticity. For all the table of price elasticity, the figures in bold are significant. The price elasticity for both formal and informal goods is negative and significant. The cross-price elasticity shows that informal and formal goods are substitutes but those estimates are almost significant. The pattern is consistent for estimates with and without the symmetry constraint. To summarize, in general, the budget share for informal goods decreases as the total expenditure level increases, and informal and formal goods are likely to be imperfect substitutes, as suggested by the first channel.

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Table 6: A: Results of Full Sample (Adjusted Channel Indicator): First Stage

	Budget Share Regressions			
	Without Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	0.000640***	-0.00307***	0.000583***	-.00306***
	(0.000)	(0.000)	(0.000)	(0.000)
$lhhs$	-0.000225***	0.000649***	-.000273***	0.000639 ***
	(0.001)	(0.000)	(0.000)	(0.000)
R^2	0.3669	0.5169	0.3452	0.5160
N	8895	14313	9494	14319
	Unit Value Regressions			
	Without Imputation		With Imputation	
β^1	0.585***	0.392***	0.557***	0.392***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.4137	0.7049	0.3772	0.7047
N	8895	14313	9494	14319
ϵ_x	0.631	0.490	0.640	0.490

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: In this section, the result tables will include only the goods we are interested in, the 'other goods' generated for completing the system are not shown here but full results can be generated by running the code. Estimates of other coefficients are available on requests.

Table 7: A: Results of Full Sample: Price Elasticity

	No Symmetry Restriction			
	With Imputation		Without Imputation	
	Formal	Informal	Formal	Informal
Formal	**-0.661**	-0.115	**-0.621**	-0.157
	(0.0586)	(0.120)	(0.0627)	(0.119)
Informal	0.0752	**-0.771**	0.0819	**-0.769**
	(0.0384)	(0.0831)	(0.0473)	(0.0816)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	**-0.766**	0.515	**-0.745**	0.530
	(0.0740)	(0.295)	(0.0890)	(0.340)
Informal	0.0605	**-0.759**	0.0619	**-0.755**
	(0.00341)	(0.0856)	(0.0392)	(0.0815)

Note: Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The standard errors for price elasticity matrices are obtained by bootstrapping, making 1000 draws from the clusters in the second stage, which is defined as half of the interval that contains 68.3 percent of the bootstrapped estimates. The estimate for price elasticity is regarded as significant if it is larger than twice the bootstrapped standard error.). There are four two-times-two matrices of price elasticity in the table. The entries with different names on rows and columns are cross-price elasticity, which is positive for substitutes and negative for complements.

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C. Staples

Table 8 shows both informal and formal staples are necessities while the expenditure elasticity is slightly higher for the informal goods, which may contribute to the higher quality elasticity of formal staples. This may suggest that consumers choose formal staples for quality more but informal staples for quantity more as total expenditure increases. The cross-price elasticity is not pinned down without imputation; the results with imputation show that formal and formal goods are complements as the third channel.

Table 8: C: Results by Categories: Staples

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	-0.004523***	-0.000902***	-0.00432***	-0.000896***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.4670	0.5917	0.4402	0.5589
N	4884	12462	5883	13635
	Unit Value Regressions			
	No imputation		With Imputation	
β^1	0.209***	0.167***	0.187***	0.158***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.5183	0.5708	0.4757	0.5374
N	4884	12462	5883	13635
ϵ_x	0.544	0.629	0.583	0.639

p-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No Imputation		Without Imputation	
	Formal	Informal	F	I
Formal	**-0.607**	-0.0431	**-0.584**	**-0.183**
	(0.057)	(0.046)	(0.12)	(0.060)
Informal	-0.0264	**-0.670**	**-0.241**	**-0.378**
	(0.05)	(0.048)	(0.059)	(0.064)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	**-0.604**	-0.0550	**-0.546**	**-0.370**
	(0.057)	(0.070)	(0.12)	(0.08)
Informal	-0.0228	**-0.691**	**-0.157**	**-0.394**
	(0.029)	(0.046)	(0.03)	(0.06)

Note: In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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D: Meat and Seafood

Table 9 shows both informal and formal meat are necessities while the expenditure elasticity is slightly higher for formal goods. The higher quality elasticity for informal goods may suggest that consumers choose informal meat for quality more as total expenditure increases. The negative cross-price elasticity with symmetry constraint suggests that informal and formal goods are complements but they are not significant.

Table 9: D: Results by Categories: Meat and Seafood

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	-0.000312	-0.000557***	-0.000286	-0.000507***
	(0.255)	(0.000)	(0.256)	(0.000)
R^2	0.6645	0.4260	0.6936	0.4090
N	620	13911	787	14971
	Unit Value Regressions			
	No Imputation		With Imputation	
β^1	0.359***	0.478***	0.338***	0.450***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.7878	0.6738	0.7726	0.6520
N	620	13911	787	14971
ϵ_x	0.538	0.442	0.563	0.478

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
Formal	**-0.915**	0.0743	**-0.974**	0.0186
	(0.071)	(0.069)	(0.095)	(0.010)
Informal	-0.0389	**-0.567**	-0.0252	**-0.659**
	(0.049)	(0.094)	(0.041)	(0.067)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	**-0.894**	-0.0451	**-0.967**	-0.0350
	(0.069)	(0.082)	(0.10)	(0.074)
Informal	-0.0196	**-0.576**	-0.0146	**0.662**
	(0.035)	(0.10)	(0.03)	(0.067)

In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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E: Dairy, Oil, Sugar, and Sauce

Table 10 shows that, for dairy products, oil, sugar, and sauce, informal goods have higher expenditure elasticity and lower quality elasticity. One unconstrained estimate of price elasticity without imputation shows that they are complements as in channel three. This pattern may indicate that informal goods in this market may be preferred by other characteristics like traditional tastes or accessibility which helps sustain their demand as total expenditure increases.

Table 10: E: Results by Categories: Dairy, Oil, Sugar, Sauce

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	-0.0003625***	-0.00105***	-0.000323***	-0.000981***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.4156	0.5057	0.4136	0.4864
N	3546	14222	4305	15259
	Unit Value Regressions			
	No Imputation		With Imputation	
β^1	0.494***	0.300***	0.463***	0.283***
	(0.000)	(0.000)	(0.0000)	(0.000)
R^2	0.5026	0.5885	0.4808	0.5673
N	3546	14222	4305	15259
ϵ_x	0.203	0.418	0.269	0.454

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No imputation		With Imputation	
	Formal	Informal	Formal	Informal
Formal	**-0.313**	**-0.411**	**-0.614**	-0.120
	(0.14)	(0.13)	(0.15)	(0.11)
Informal	0.0351	**-0.763**	-0.0702	**-0.839**
	(0.062)	(0.08)	(0.052)	(0.059)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	**-0.416**	-0.00933	**-0.600**	-0.189
	(0.12)	(0.15)	(0.122)	(0.12)
Informal	-0.00304	**-0.729**	-0.0614	**-0.844**
	(0.05)	(0.066)	(0.038)	(0.055)

In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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F: Vegetables and Fruits

Table 11 shows that for vegetables and fruits, formal goods have higher expenditure elasticity, and the quality elasticity is similar for informal and formal goods. The positive estimates of cross-price elasticity in all estimations show that they are imperfect substitutes, though they are insignificant. This may be consistent with the first channel, suggesting that informal goods may be preferred as imperfect substitutes because of income inequality and their budget share decreases much more quickly than formal goods as total expenditure increases.

Table 11: F: Results by Categories: Vegetable and Fruits

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	-0.000235	-0.00279***	-0.000117	-0.00263***
	(0.18)	(0.000)	(0.481)	(0.000)
R^2	0.7392	0.5947	0.7334	0.5555
N	505	13829	621	14908
	Unit Value Regressions			
	No Imputation		With Imputation	
β^1	0.166*	0.185***	0.224**	0.173***
	(0.073)	(0.000)	(0.012)	(0.000)
R^2	0.7445	0.6741	0.7419	0.6443
N	505	13829	621	14908
ϵ_x	0.649	0.442	0.681	0.475

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No imputation		With Imputation	
	Formal	Informal	Formal	Informal
Formal	**-0.858**	0.136	**-0.867**	0.145
	(0.14)	(0.15)	(0.18)	(0.21)
Informal	0.0628	**-0.594**	0.109	**-0.752**
	(0.092)	(0.087)	(0.11)	(0.082)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	**-0.882**	0.322	**-0.917**	0.523
	(0.17)	(0.40)	(0.21)	(0.42)
Informal	0.0553	**-0.590**	0.0872	**-0.744**
	(0.069)	(0.081)	(0.07)	(0.075)

In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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G: Non-alcoholic Beverage

Table 12 shows that informal and formal goods have similar expenditure elasticity and constrained estimates with imputation suggest that they are imperfect substitutes. The coefficient of lnx is less negative for informal goods, suggesting their budget share decreases more slowly than formal goods as total expenditure increases. These may suggest that demand for informal goods may come from the second channel and informal goods may be preferred for other properties. The results may be interpreted with caution given the limitations of imputation.

Table 12: G: Results by Categories: Non-alcoholic Beverage

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	-0.000231***	-0.000106***	-0.000219***	-0.0000665***
	(0.000)	(0.000)	(0.000)	(0.021)
R^2	0.3148	0.3529	0.3463	0.3277
N	1872	9873	2284	11156
	Unit Value Regressions			
	No Imputation		With Imputation	
β^1	0.264***	0.426***	0.236***	0.394***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.4191	0.4543	0.4306	0.4217
N	1872	9873	2284	11156
ϵ_x	0.465	0.473	0.515	0.543

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No imputation		With Imputation	
	Formal	Informal	Formal	Informal
Formal	-0.157	0.0906	**-0.524**	0.114
	(0.20)	(0.12)	(0.24)	(0.11)
Informal	0.169	**-0.189**	**0.406**	**-0.453**
	(0.16)	(0.094)	(0.21)	(0.12)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	-0.170	0.157	**-0.586**	**0.286**
	(0.18)	(0.14)	(0.24)	(0.13)
Informal	0.128	-0.177	**0.238**	**-0.402**
	(0.11)	(0.09)	(0.11)	(0.10)

In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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H: Alcoholic Beverage

Table 13 shows a pattern similar to that of non-alcoholic beverages, except that the coefficient of lnx for formal beverages is positive but not significant. The expenditure elasticity without quality effects is similar for informal and formal goods. The unconstrained estimates with imputation show a significant and positive cross-price elasticity, suggesting that they are imperfect substitutes.

Table 13: H: Results by Categories: Alcoholic Beverage

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	0.0000781	-0.000137**	0.0000917	-0.0000785
	(0.675)	(0.030)	(0.627)	(0.187)
R^2	0.5684	0.3341	0.5821	0.2862
N	584	4696	687	5439
	Unit Value Regressions			
	No Imputation		With Imputation	
β^1	0.585***	0.471***	0.548***	0.429***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.7791	0.5696	0.7472	0.5082
N	584	4696	687	5349
ϵ_x	0.466	0.449	0.508	0.525

p-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No imputation		With Imputation	
	Formal	Informal	Formal	Informal
Formal	**-0.674**	0.166	**-0.695**	**0.339**
	(0.12)	(0.11)	(0.10)	(0.12)
Informal	0.0176	**-0.762**	0.00787	**-0.749**
	(0.087)	(0.08)	(0.073)	(0.073)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	**-0.656**	0.0722	**-0.698**	0.121
	(0.011)	(0.074)	(0.10)	(0.067)
Informal	0.0654	**-0.778**	0.116	**-0.745**
	(0.066)	(0.08)	(0.064)	(0.072)

In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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I: Clothing

Table 14 shows that the coefficient of lnx for informal goods is positive, and expenditure and quality elasticities of income are higher for informal goods. We may expect informal goods to be preferred for other attributes, helping their demand to be more sustainable. However, estimates of price elasticity are not significant due to the limitations in using unit values for non-foods as a proxy for prices.

Table 14: I: Results by Categories: Clothing

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	-0.000848*	0.000414	-0.000659	0.00298
	(0.072)	(0.168)	(0.128)	(0.300)
R^2	0.6355	0.4452	0.6898	0.4261
N	450	2327	540	2743
	Unit Value Regressions			
	No Imputation		With Imputation	
β^1	0.386***	0.516***	0.388***	0.434***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.6907	0.4033	0.7029	0.3590
N	450	2327	540	2743
ϵ_x	0.421	0.579	0.466	0.630

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No imputation		With Imputation	
	Formal	Informal	Formal	Informal
Formal	-0.511	0.0536	-0.290	-0.218
	(0.55)	(0.25)	(0.66)	(0.48)
Informal	0.309	-0.448	0.241	-0.253
	(0.91)	(0.43)	(0.54)	(0.45)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	-0.554	0.173	-0.348	0.0407
	(1.13)	(0.58)	(1,12)	(0.55)
Informal	0.172	-0.404	0.0383	-0.197
	(0.58)	(0.39)	(0.53)	(0.41)

In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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L: Transportation

Table 15 shows that the coefficient of lnx is positive for both informal and formal goods, suggesting that the budget for transportation is increasing in total expenditure. The lower quality elasticity of income and higher expenditure elasticity for informal goods suggest that consumers may prefer informal transportation more for quantity as total expenditure increases. The estimates indicate that informal and formal transportation are complements, but these are not significant.

Table 15: L: Results by Categories: Transportation

	Budget Share Regressions			
	No Imputation		With Imputation	
	Formal	Informal	Formal	Informal
lnx	0.000535*	0.000245*	0.000339	0.000299**
	(0.089)	(0.082)	(0.277)	(0.024)
R^2	0.4938	0.5743	0.5000	0.5388
N	366	2219	432	2639
	Unit Value Regressions			
	No Imputation		With Imputation	
β^1	0.518***	0.306***	0.451***	0.323***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.8092	0.6151	0.7748	0.5841
N	366	2219	432	2639
ϵ_x	0.772	0.811	0.739	0.817

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Price Elasticity			
	No Symmetry Restriction			
	No imputation		With Imputation	
	Formal	Informal	Formal	Informal
Formal	**-0.472**	-0.010	**-0.596**	-0.0310
	(0.14)	(0.056)	(0.17)	(0.10)
Informal	-0.304	0.324	-0.155	0.0493
	(0.22)	(0.25)	(0.16)	(0.24)
	With Symmetry Restriction			
	Formal	Informal	Formal	Informal
Formal	**-0.411**	-0.159	**-0.564**	-0.108
	(0.14)	(0.10)	(0.15)	(0.10)
Informal	-0.139	0.270	-0.0901	0.0226
	(0.087)	(0.24)	(0.09)	(0.21)

In the regressions for decomposed categories, the channel indicator used is the adjusted channel indicator. Bootstrapped standard error in parentheses. Price elasticity is significant if in bold (The price elasticity is larger than twice the bootstrapped standard errors in magnitude).

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7.2 Discussion

Based on the result for the full sample, we can know that on average, the informal sector shrinks as the aggregate income level increases. Before the income level increases to a certain threshold, policies to promote formality from the supply side may not be as effective as they were expected to be because the large demand for low-quality and cheaper informal goods resulting from income inequality attract potential entrepreneurs into the informal sector. For markets where demand for informal goods follows the second and third channels, the demand may sustain for a longer time as the economy develops. In this case, the policy to improve formality can focus more on reducing the registration costs and regulation costs of traditional shops or informal firms, allowing them to maintain their production as formal firms, rather than pushing their transformation into industrialized producers.

8. Results

This paper studies the demand pattern for informal goods in Africa using household-level survey data from the Democratic Republic of the Congo in 2012. There are three major factors driving the demand for informal goods: income inequality, quality preference, and preference for product-specific characteristics. I hypothesize that there are mainly three channels of demand for informal goods and use the empirical method proposed by Deaton (2018) to test them by estimating expenditure elasticity, price elasticity, and quality elasticity. The empirical results suggest that budget shares for informal goods decrease as total expenditure increases. The pattern can be different for different categories of goods. Informal goods and formal goods can be either imperfect substitutes or complements in the final good markets, and the demand for some informal goods can sustain as income increases because they are preferred for their own features. Policies to improve formality can adjust according to the demand pattern in different markets to improve policy effectiveness. This paper also discussed how the empirical method is conducted under assumptions and is subject to several limitations, which may be improved in the future.

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Article

Negotiating Justice: Examining Restorative Justice Through the Coase Theorem

Andrei Comlosan-Pop[1]

[1] Student (BA Economics, 2021-25), Harvard University, USA; acomlosanpop@college.harvard.edu

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Abstract
Restorative justice differs markedly from the traditional law-and-economics model of crime and punishment, as it eschews deterrence-based punishment and grants a far greater role to victims of crime. Existing economic literature on restorative justice is limited, and this increasingly popular paradigm warrants further law-and-economics engagement. This paper adopts a novel approach by using the Coase Theorem to analyze restorative justice negotiations as an alternative that victims and offenders may choose to traditional criminal procedures. I conclude that, with the proper enabling conditions, restorative justice can lead to higher victim and offender welfare compared to traditional criminal procedures by lowering the transaction costs to bargaining and by granting the victim a clear legal entitlement. However, differences in existing programs, behavioral economics principles, and concerns from beyond the economic literature suggest that maximally efficient outcomes may not occur in real life.

Keywords: Restorative Justice; Coase Theorem; Welfare; Behavioural Economics

1. Introduction

For individuals disillusioned with a traditional punitive model of criminal justice, restorative justice represents an enticing alternative. Restorative justice is '"an approach to achieving justice that involves"' having those implicated in an offense '"collectively identify and address harms, needs, and obligations, in order to heal and put things as right as possible"' (Zehr 2002, qtd. in Lanni 2021, 641-42). This process is sometimes described in terms of four Rs: 'repair, restore, reconcile, and reintegrate' (Menkel-Meadow 2007, 10.2). Pioneered by figures such as John Braithwaite, the 'modern incarnation' of restorative justice arose in the 1970s as a reaction to the perceived failures of the justice system to '[deter] crime' and 'successfully rehabilitate offenders' (Ibid., 10.3).

In the criminal system, a restorative vision of justice 'typically' entails interaction between the victim, offender, and potentially other members of the community (Lanni 2021, 637), with facilitation from professionals or volunteers. For offenders, participating in restorative justice can divert a case away from the traditional trial process, serve as a form of sentencing in and of itself, or help reduce a sentence (Ibid.). Restorative justice also offers victims the opportunity to receive an offender's acknowledgement of wrongdoing and the process may entail specific steps of restitution for the offender to take (643, 646). Offender participation in a restorative justice process is 'usually not mandatory' (654), and victims generally exercise a form of 'veto power' over its employment (Fatas and Restrepo-Plaza 2022, 2; see also Lanni 2021, 668). Restorative justice is used around the world as a diversion from or supplement to traditional criminal justice approaches, including in juvenile systems in Australia (Shem-Tov, Raphael, and Skog 2021, 7) and Indonesia (Subekti, Hartiwiningsih, and Handayani 2021, 56), and in both juvenile and non-juvenile systems in New Zealand (Shem-Tov, Raphael, and Skog 2021, 7; New Zealand Sentencing Act 2002 (2022); Lanni 2021, 650), Colombia (Fatas and Restrepo-Plaza 2022, 2), and South Africa (Department of Justice and Constitutional Development 2011, 7-8).

As a significant departure from the traditional, rational-choice law-and-economics prescriptions for punishment, restorative justice warrants an economic study. In the former, criminality is a cost-benefit analysis between expected gain and sanction, and the state crafts sanctions to maximize the benefits of deterrence against the costs of law enforcement (see Polinsky and Shavell 1984, among others). In contrast, restorative justice sees crime as a relational problem requiring interpersonal solutions and therefore facilitates reconciliation between the affected parties (see Zehr 2002, qtd. above in Lanni 2021). Another significant disparity between the two frameworks is the role of victims. The rational-choice law-and-economics model does not see the victim as an agent in the criminal justice process. Prosecutors and judges may, by custom or statute, consult victims about plea bargaining or sentences (formalized, in the case of the latter, through victim impact statements), but victims nevertheless lack a clear entitlement to inform the process. Restorative justice affords far greater agency to the victim and sees victim participation as integral to the justice process (Lanni 2021, 642-43). An economic exploration of restorative justice allows us to understand how these differences impact societal welfare.

In this paper, I use the Coase Theorem to analyze whether allowing victims and offenders to choose restorative justice as an alternative to traditional criminal prosecution promotes economic efficiency. I define the Coase Theorem as stating that: under conditions of economic rationality where parties are ready and willing to bargain and do in fact bargain and reach an agreement, entitlements will always move toward their highest-value use, regardless of their initial allocation, provided that there are no (or minimal) transaction costs and property rights are clearly defined (Coase 1960)[1]. Ronald Coase developed the analysis undergirding the Coase Theorem in the context of legal liability, demonstrating the economic irrelevance of such rules in situations of free, rational bargaining over entitlements. The Coase Theorem is thus a useful framework for conceptualizing restorative justice as a process of negotiation and as one which can partly internalize the externalities of crime. I also define efficiency to mean the maximization of the private welfare of the parties directly involved in the negotiation—victims and offenders. While I briefly comment on the implications of restorative justice for deterrence and recidivism, a thorough analysis of these and other aspects of social welfare exceeds the space available in this paper.

Literature applying an explicit law-and-economics lens to restorative justice is, so far, limited. Bush (2003), who uses this lens to emphasize the shortcomings of the restorative justice paradigm, offers the most thorough treatment. I contribute to the literature by analyzing restorative justice through the Coase Theorem, demonstrating the potential advantages of restorative

[1] The underlying analysis was first expounded in Coase's 1960 paper, 'The Problem of Social Cost,' although George Stigler was the first to summarize Coase's reasoning and call it a 'Theorem' (Carden 2020, 45).

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justice from an economic perspective. To my knowledge, the Coase Theorem has not been used thus far in the English literature to conceptualize restorative justice.[2]

I conclude that, given the proper enabling conditions, the option to resolve a case through restorative justice instead of traditional criminal prosecution leads to more negotiated outcomes between victims and offenders and to outcomes that are better for the parties, thus promoting economic efficiency. Restorative justice achieves this result by lowering the transaction costs to bargaining and by helping internalize the externalities of crime borne by victims. However, transaction costs likely remain even under formal restorative justice programs, and preconditions to negotiation may prevent parties from ever choosing to bargain. Insights from behavioral economics and non-economic literature suggest further reasons why restorative justice negotiations may deviate from Coasean ideals. Consequently, in practice, restorative justice programs may not create maximally efficient outcomes for victims and offenders.

2. Literature Review

The existing law-and-economics literature on restorative justice is limited. Bush's (2003) major treatment gives restorative justice a 'mixed review' (441). In one major critique, he contends that victims should not be satisfied by restorative efforts (459), because 'compensation cannot occur on any significant level in criminal law' (464). Even direct compensation for a crime would not leave the victim as well off as they would have otherwise been, due to the wide variety of costs which crime imposes on its victims (e.g., direct costs, increased expenditure on preventing future crime, and the costs, emotional or otherwise, of participating in a criminal justice process). Thus, Bush interprets the empirical evidence that victims are satisfied with restorative justice as a sign that they are incorrectly comparing their outcomes under restorative justice with outcomes under the criminal justice system, whereas the proper comparison is with a pre-crime state (459).

Here, Bush wrongly conflates satisfaction with indifference between states of utility. While a victim may not be indifferent between their utility before the crime and after restorative justice, their utility may nonetheless rise from a post-crime level through restorative justice. A victim could thus rationally say they are satisfied with the process without being made whole, if the starting point is post-crime, rather than pre-crime as Bush imagines it.

Bush further argues that, despite its claims, restorative justice cannot feasibly compensate a community for the impacts of crime. Crime ripples out from the direct victim in ways which may be too complex for restorative justice to address (461-64). This is an important limitation on the welfare impacts of restorative justice: some parties who were harmed by a crime may indeed be left out of a restorative process. But as the number of participants grows, so do the transaction costs. Limiting the participants to those most directly affected by the crime—the victim and the offender—could thus be conducive to a successful agreement, a logical extension of my Coasean analysis below.

Another important consideration for social welfare is the effect of restorative justice on deterrence. Bush argues that a restorative justice model focused solely on victim compensation would severely weaken, if not eliminate, deterrence, as it results in expected penalties that are too low to dissuade potential offenders (464-65). While Bush is correct that employing restorative justice will result in some offenders receiving lesser sanctions than under a purely retributive system, his analysis assumes that restorative justice would completely replace retributive justice. In a model where restorative justice is an optional alternative requiring victim consent, a potential offender cannot rely on having a victim that is amenable to restorative justice. Thus, the expected penalty will continue to include the potential for traditional criminal sanction, mitigating the drop in deterrence. Adding a restorative element to the justice system may also '[enhance] the community's perception of' the justice system; this makes the public more likely to cooperate with police, increasing the probability of apprehension and mitigating a drop in deterrence (Lanni 2021, 678).

At the same time, Bush sees restorative justice as improving upon traditional criminal processes through lower recidivism rates (464). This conclusion is supported by Shem-Tov, Raphael, and Skog (2021), who conclude that juvenile offenders assigned to

[2] A Russian-language article may apply a similar idea, but only the title and abstract are available in English. The paper's title is 'Use of Rational Choice Theory in Criminal Law and Criminology (On the Example of the Coase Theorem)

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a restorative justice program in San Francisco are 32% less likely to be rearrested four years post-intervention compared to non-assigned offenders (2). This result may stem from 'preference shaping devices' in the restorative justice process (Bush 2003, 467). These include 'fostering empathy and dialogue with the victim' (Shem-Tov, Raphael, and Skog 2021, 2-3), and therapy programs that can address how offenders weigh the impacts of their actions and can raise awareness about social supports that eliminate the need to resort to crime (Bush 2003, 468).

Other research characterizes restorative justice as a form of private economic ordering, which is used in lieu of government intervention to achieve an efficient result (Subekti, Hartiwiningsih, and Handayani 2021, 59; Lawson and Katz 2004, 179).[3] This is a helpful lens through which to see restorative justice, and naturally suggests the Coase Theorem as an analytical framework. Some theorists add that restorative justice relies on 'social capital,' a concept which Artinopoulou (2016) defines as 'the social bonds, links, networks and connections that bind families, communities and societies' (119). As one example of this exchange of social capital, Bibas and Bierschbach (2004) argue that crime creates a 'moral imbalance' (110) between the offender, and their victim and community (91), as the offender rejects the community's rules and denies that the victim 'deserve[s] respect' (110; see also Mamo 2019, 1447, and Lanni 2021, 646). An apology in this situation 'both teach[es] and reconcile[s] by reaffirming societal norms and vindicating victims' (Bibas and Bierschbach 2004, 113), an opportunity that is largely absent in the current legal system (136). The theories of social capital and apology as moral restitution can explain how Coasean negotiation provides benefits to victims and allows for the trading of valuable psychic goods.

Empirical findings on restorative justice outcomes also indicate benefits to victims and offenders. Strang et al. (2013) conduct a meta-analysis on 15 studies of restorative justice conferencing, concluding that victims who were assigned to restorative justice procedures had 'consistently higher' satisfaction reports than victims who were assigned to traditional criminal procedures (47). They also find a statistically significant decrease in recidivism for participants in restorative justice (25). Wilson, Olaghere, and Kimbrell (2017) review 84 evaluations in their meta-analysis, focusing on restorative justice with youth offenders. They conclude that victims who went through restorative justice had greater 'perceptions of fairness and greater satisfaction, … and [were] more likely to feel that the outcome was just' (3). Offenders similarly 'had a greater perception of fairness' (3), were 'more satisfied with the program than youth in the comparison conditions' (38), and had a 'moderate reduction in future delinquent behavior' compared to youth who did not participate in restorative justice (6).

However, study design issues in each meta-analysis limit the generalizability of their results. Strang et al. (2013) only include studies in which victims and offenders agreed to be randomly assigned to restorative justice or an alternative before assignment to treatment or control groups occurred (12). Victims and offenders who agreed to randomization likely differ systematically from the population. Given this, Strang et al. may only indicate that restorative justice is more satisfying among individuals favorably disposed to restoration in the first place. Wilson, Olaghere, and Kimbrell (2017), on the other hand, include restorative justice programs without direct contact between offenders and victims and do not distinguish between different program types when presenting their findings on victim and offender satisfaction (34-35). Thus, their results do not offer a clear evaluation of victim-offender negotiation, although they do indicate that restorative justice generally construed is beneficial for victims and offenders.

An even larger issue arises from underlying studies in both meta-analyses using different control groups. In Strang et al. (2013), the control conditions include traditional prosecution, other diversion programs, or simply not employing restorative justice (in studies where the interventions were post-plea or post-sentence) (20-21). Wilson, Olaghere, and Kimbrell (2017) include studies where the control group was either a 'traditional' criminal justice process or 'an alternative program' (21). Due to these inconsistent comparators, the meta-analyses do not provide a definitive answer as to how restorative justice improves upon alternative options, or upon which alternatives it most improves.

Finally, Fatas and Restrepo-Plaza (2022) conduct an experiment to test the impact of various behavioral interventions on the willingness of participants to forgive offenders. The authors framed the decision to forgive as a risky choice between the benefits of rehabilitation and the costs of reoffending (2-3). For some participants, the risk was presented as the loss of an initial endowment if the offender recidivates, while for others, it was framed as a potential gain if the offender does not recidivate (3).

[3] Subekti, Hartiwiningsih, and Handayani (2021) also write that restorative programs with a diversionary element are 'a manifestation of the transaction cost of economy [sic]' (59), although the rest of their article indicates that they may have administrative costs in mind.

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Fatas and Restrepo-Plaza find that participants are more willing to forgive when their choice is framed as a potential loss, rather than a potential gain (8), in accordance with the predictions of prospect theory.[4] This work indicates how behavioral economics concepts may build on a purely rational assessment of restorative justice.

I contribute to the economic study of restorative justice by analyzing this process through the Coase Theorem. I thus extend the law-and-economics work in Bush (2003) and incorporate insights on the nature of restorative justice from non-economic research identified above. I add nuance to my analysis by considering the impact of behavioral economics principles on restorative justice negotiations. My Coasean analysis also provides a testable theory as to the expected impacts of restorative justice for further empirical research.

3. Materials and Methods

This paper focuses on the discussions between victims and offenders that take place in many restorative justice programs and how they change the welfare of both parties. As noted above, the wider question of efficiency in the justice system, which may be defined as maximizing social welfare, is beyond the scope of this paper. I further limit my focus to forms of restorative justice that involve direct interaction between victim and offender and to crimes with a high degree of personal interaction, including non-fatal violent crime and property crime (e.g., burglary and theft; see Shem-Tov, Raphael, and Skog 2021, 1).

I rely on rational-choice economic theory in this analysis, which assumes that humans rationally seek to maximize their own utility. After presenting my first-stage analysis, I address how the behavioral economic concepts of optimism bias, self-serving bias, bounded self-interest, the endowment effect, and prospect theory could impact my conclusions.

My analysis has six further assumptions. (i) Restorative justice occurs if both the victim and offender choose to participate; they are the only parties in the negotiation. This is often not the case in practice, as participants from the wider community may be involved. (ii) Offenders are guilty of the offenses with which they are charged and are willing to admit the same, given the right incentives. Thus, there are no Type 1 (false positive) error costs. (iii) Restorative justice occurs before a finding of guilt. Restorative justice programs today may also occur as part of sentencing or post-sentencing (Lanni 2021, 649-50). (iv) The offender and victim hold on to their entitlements until they agree on the proper way to divide the cooperative surplus. Some restorative justice programs employed today may require the surrender of some entitlements before the process even begins. (v) If successful, restorative justice replaces a traditional criminal prosecution. However, if either the victim or the offender chooses to forego restorative justice or the process fails to result in an agreement, the case is resolved through ordinary criminal procedures. South Africa, for instance, operates a similar diversionary model, although prosecutors decide whether to refer a case for restorative justice and whether to accept a restorative justice agreement (Department of Justice and Constitutional Development 2011, 7). (vi) Finally, there is no other party (e.g., a presiding judge) who can modify or invalidate a restorative agreement reached by the victim and offender. In practice, this may be true for diversionary restorative justice processes but may not be the case when restorative justice is used as part of sentencing (657-658).

4. Results

There are four conditions that must be met for the predictions of the Coase Theorem to hold: (i) rights to entitlements must be clearly defined; (ii) parties must be able and willing to bargain; (iii) there must be no or minimal transaction costs; and (iv) parties must in fact bargain and come to an agreement. Conditions (i) and (iii) are explicitly stated by Ronald Coase in his seminal article (Coase 1960, 15, 19). Conditions (ii) and (iv) are implicit to a successful negotiation process. I analyze each of these conditions in turn, after first identifying the entitlements at play in restorative justice.

[4] Prospect theory is a behavioral economic theory of valuation positing that: humans assess changes to wealth (i.e., any entitlement they possess) relative to a reference point; a gain of a given amount brings less utility than a loss of the same amount brings disutility (i.e., loss aversion); and, due to the foregoing, individuals are risk-seeking for losses but risk averse for gains (see Thaler (2015))

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The offender has a legal entitlement and two moral entitlements. In the United States context, the offender's legal entitlement is their Sixth Amendment right to contest the charges against them.[5] Their moral entitlements are the ability to grant an apology that a victim may desire and the ability to make restitution for the crime; the two are closely linked, as making amends for the crime validates the sincerity of contrition. The offender's three entitlements exist in both a traditional criminal justice process and a restorative justice process.

Victims, on the other hand, do not have a true entitlement under the traditional criminal justice system. While prosecutors or judges may solicit their perspectives pursuant to custom or statute, victims lack the ability to determine the trajectory of their case. Under restorative justice, however, victims 'typically' 'hold a de facto veto power' over case resolution (Lanni 2021, 668; Fatas and Restrepo-Plaza 2022, 2). Thus, their legal entitlement is the ability to provide a more favourable outcome to the offender by consenting to a restorative justice agreement. Victims also have the moral entitlement to accept the offender's apology.

The expected value of trial as the next-best alternative for either party determines the value of entitlements. The defendant will not surrender their entitlements if doing so costs them more (in utility terms) than they expect a trial to cost. The expected cost of trial is the highest price an offender would be willing to pay under restorative justice. Similarly, a victim would not accept an agreement that benefits them less than they expect to benefit from a trial. The victim's net utility gain from trial informs the minimum terms they would be willing to accept in a restorative justice agreement.

> (i) Rights to these entitlements are, in general, clearly defined. Neither party can be forced to surrender their moral entitlements; the legal entitlement of the offender to contest charges stems from the Sixth Amendment to the United States Constitution; and victims may veto the use of restorative justice in many situations. However, some programs may not guarantee this veto power to the victim. Furthermore, offenders may require statutory protections to access restorative justice without penalty. Massachusetts, for example, prohibits using participation in restorative justice or the offender's statements during such a process as evidence or 'an admission of guilt' (Lanni 2021, 655, quoting Mass. Gen. Laws ch. 276b, § 4 (2018)). Without such protections, defendants must choose between accessing restorative justice and avoiding self-incrimination. Thus, rights to entitlements may not be sufficiently clear in all restorative justice contexts.
>
> (ii) Restorative justice programs provide a formal venue that enables offenders and victims to bargain over their entitlements. This is in contrast to a traditional criminal justice process, where there is likely no established means through which offenders and victims can interact before the trial concludes. However, even with the ability to bargain, not all offenders and victims may be willing to do so. The victim may have a strong desire to see the defendant punished, and the offender may believe that they can avoid a guilty verdict in the first place, or they may simply be unwilling to accept responsibility under any circumstances. In such cases, the expected benefits of restorative justice would not exceed the expected benefits of trial, and restorative justice bargaining would not occur.

Nevertheless, there are potential gains under restorative justice that would lead some parties to bargain. The offender may receive a more favourable disposition through restorative justice than through a traditional criminal process, which strongly incentivizes their participation. The victim could avoid the disutility of a trial, resolve their case more quickly, and receive an apology and restitution. In these situations, the expected value of restorative justice to both parties exceeds the expected value of trial, and the parties would negotiate.

> (iii) Compared to traditional criminal procedures, restorative justice programs lower the transaction costs for victims and offenders to negotiate over their entitlements, as the parties no longer bear the logistical expenses required to coordinate such a negotiation. Some transaction costs would remain, such as the emotional cost of revisiting the crime and the time cost of participating. But since these types of costs also exist under the traditional criminal justice system, restorative justice represents a net decrease in transaction costs for the parties.

[5] Prospect theory is a behavioral economic theory of valuation positing that: humans assess changes to wealth (i.e., any entitlement they possess) relative to a reference point; a gain of a given amount brings less utility than a loss of the same amount brings disutility (i.e., loss aversion); and, due to the foregoing, individuals are risk-seeking for losses but risk averse for gains (see Thaler (2015)).

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(iv) Provided that the victim and offender do engage in negotiation and their reservation prices (i.e., the 'price' each is willing to accept or pay to give up their entitlements) overlap for some mutually acceptable outcomes, they should reach an agreement. The Coase Theorem does not predict the precise division in cooperative surplus between victim and offender, but under conditions of rationality, any agreement within the settlement range would be acceptable to both parties. Once a restorative agreement is reached, the offender accepts responsibility and commits to certain actions to make amends, surrendering their entitlements, and the victim consents to the resolution of the case through such actions and surrenders their entitlements. The surrender of entitlements also signals that the welfare of each party is higher than it would have been under a traditional criminal process.

This negotiation demonstrates how restorative justice helps internalize the externalities of crime and criminal justice. An external cost, or externality, is a negative consequence of some main economic transaction. In Coase's (1960) classic example of a cattle rancher and farmer, the victim of the cattle ranching is the farmer—but the rancher's goal is to grow cattle, not to harm the farmer. Similarly, non-fatal violent crime and property crime functions as an economic transaction where the offender unlawfully takes some tangible or intangible good, such as stealing a valuable object. Even acts that physically harm the victim may simply use the victim's body to attain a wider goal, like instilling fear. The emotional, monetary, and other impacts on the victim are the externalities. The traditional criminal justice process also imposes externalities on victims. Choices made by prosecutors and defendants result in costs to the victim. For instance, while the victim may prefer to avoid testifying at trial, they may have to incur emotional and time costs to appear on the stand if the defendant contests the charges. An adversarial process fails to internalize these two sets of externalities and thus leads to economic inefficiency.

In a restorative justice process, the victim's ability to negotiate with the offender and determine the outcome of their case allows them to fully bring their externalities into the discussion. The negotiating parties directly address the costs to the victim when forming the restorative justice agreement, thus helping to mitigate the externalities of crime. The victim can also avoid the costs of trial by entering into a restorative justice agreement, resolving an additional externality problem that would be present in the traditional system.

5. Discussion

If the four conditions above hold, the Coase Theorem predicts that the victim's and offender's entitlements have moved to their highest-value use. Thus, adding the option to pursue restorative justice instead of traditional criminal prosecution promotes economic efficiency by raising the welfare of offenders and victims. Importantly, no offender or victim would be worse off in my model than in the criminal justice status quo since a failed negotiation would simply return a case to the traditional process.

My conclusion addresses part of the critique of restorative justice in Bush (2003), showing that victims can be rationally satisfied under restorative justice because of how the process internalizes the crime- and trial-related externalities that they face. It also provides an explanation for the findings in Strang et al. (2013) and Wilson, Olaghere, and Kimbrell (2017) that restorative justice benefits victims and offenders.

A Coasean framework shows that the efficiency benefits of an optional restorative justice process arise in large part from two key features. The first is that restorative justice programs reduce the transaction costs that victims and offenders face in negotiating: they remove the logistical burden of coordinating these types of discussions and shift the expense onto the program provider. Furthermore, restorative justice grants the victim a clear legal entitlement, allowing them to them direct the outcome of their case and internalize their crime-related externalities. Victims who expect greater benefits from avoiding, rather than participating in, a trial can negotiate with the offender to obtain these benefits. Such an entitlement does not exist in the current system.

However, the conditions for Coasean bargaining may not always be present in real-world settings. There may be high transaction costs due to the requirements of a restorative justice process. Indeed, in restorative justice programs, rates of victim participation 'at or below fifty percent are not uncommon, and … rarely exceed eight percent,' often due to 'the time and effort involved' in participating (Lanni 2021, 662). A further challenge could be that a victim's legal entitlement is unclear because their control over the process is poorly defined. Either of these possibilities threatens an ideal Coasean resolution.

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Another complication is that restorative justice programs may require the offender to surrender one or more of their entitlements as a precondition to participation. Programs 'typically require the offender to accept responsibility' (Lanni 2021, 654) at the start of the restorative process—a surrender of their moral entitlement. In such cases, the defendant retains their legal entitlement (i.e., the right to contest the charges), and the parties may still bargain over the resolution of the trial. But some programs go one step further and require the defendant to formally plead guilty before restorative justice negotiations occur. One jurisdiction with this model is New Zealand (Lanni 2021, 650, 656-57). In this case, the defendant must give up both a moral entitlement and a legal entitlement to participate. This may decrease the defendant's expected value from engaging in restorative justice, making it less likely that the defendant will enter the process in the first place and thus less likely that the efficiency benefits of restorative justice will be realized.

Furthermore, behavioral economics principles of optimism bias, self-serving bias, bounded self-interest, and the endowment effect suggest that optimal Coasean exchange is less likely in the real world compared to a perfectly rational world as the reservation prices and bargaining attitudes of the parties may not reflect what is in their rational self-interest. Prospect theory also provides insights into how the framing of restorative justice impacts the likelihood of success.

Optimism bias, as defined by Jolls (2004), is a cognitive bias whereby individuals 'underestimate the probability that negative events will happen to them as opposed to others' (4). Optimism bias could induce offenders to overestimate their chances of a favourable outcome at trial; they would then demand a more lenient restorative justice agreement. Such an outcome is particularly likely since the prosecution's standard of proof (i.e., beyond a reasonable doubt) is very high. Self-serving bias, as defined by Babcock and Loewenstein (1997), leads parties 'to conflate what is fair with what benefits oneself' (110). A related concept is bounded self-interest, defined as when one's utility function depends in part on the utility of others (Jolls, Sunstein, and Thaler 1998, 1479). One implication of this idea is that individuals may reject outcomes that are in their self-interest but nonetheless do not appear fair to themselves or others (Ibid.). Applied to restorative justice, self-serving bias and bounded self-interest would lead parties to reject offers that would be in their rational self-interest but are less than what is perceived to be fair. This narrows the range of mutually acceptable outcomes, and in extreme situations may eliminate the settlement range altogether (Babcock and Loewenstein 1997, 110).

The endowment effect predicts that economic actors value a particular good or entitlement more when they possess it than when they need to obtain it (Jolls, Sunstein, and Thaler 1998, 1484). In other words, the amount they are willing to accept to surrender an entitlement is higher than the amount they would be willing to pay to gain the same entitlement (Ibid.). As a result, the initial endowment of entitlements affects their ultimate allocation (1483). In the context of restorative justice, the endowment effect would make optimal Coasean outcomes less likely. As victims and offenders demand higher prices for giving up their own entitlements than they would pay to gain the entitlement, the settlement range grows narrower or disappears.

Finally, as demonstrated by Fatas and Restrepo-Plaza (2022), framing the choice to engage in restorative justice—specifically, to forgive an offender—as a potential loss rather than a potential gain improves the likelihood that a victim will participate. This is consistent with prospect theory (see note 4 for a definition). While participants in the study occupied the role of a victim, the same results may hold for offenders. Thus, Fatas and Restrepo-Plaza's findings suggest that the Coasean outcome of a restorative justice process can be made more likely by emphasizing the benefits that the parties may lose if they fail to participate.

In addition to these concerns from behavioral economics, non-economic literature provides additional reasons why restorative justice in practice may deviate from an ideal Coasean outcome. Restorative justice programs include the potential for victims to feel 'coerced' to accept a restorative agreement and eschew justice through traditional criminal procedures, while offenders may also feel 'coerced' to surrender their entitlements (Menkel-Meadow 2007, 10.5). In economic terms, such coercion may mean that victims and/or offenders accept restorative outcomes that do not maximize their welfare. There are additional concerns about the social implications of a model which allows for private resolution of offenses, such as whether disparate outcomes for 'similarly situated' victims and offenders challenge legal 'equality,' and whether the normative and 'precedent-setting' role of the legal system is lost when crime resolution becomes privatized (Ibid., 10.6). This set of concerns bears on the social welfare effects of restorative justice through its impact on deterrence.

Further research may test my theoretical conclusions with real-world data. Another line of future inquiry would be how the option to pursue restorative justice impacts the welfare costs of Type I errors, as innocent offenders and their 'victims' may also

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find themselves in this process. There is also a need to model the wider social welfare effects of restorative justice through its impacts on deterrence and recidivism, which merits further study but was not the primary focus of this paper.

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