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Citation Gender Gaps in Top Economics Journals*

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Abstract

This paper investigates the existence and drivers of gender citation gaps in the five leading journals in economics. Using a comprehensive dataset of 7,244 articles published between 1999 and 2023, we examine whether female-authored papers are cited more frequently than male-authored ones, and whether this pattern persists after controlling for differences in research topics. We apply Structural Topic Modeling (STM) to abstracts to estimate latent research themes and complement this approach with field classifications based on JEL codes. Our results show that female-authored papers initially display a citation premium—receiving up to 16 log points more citations—but this advantage becomes statistically insignificant once we control for research field composition using either STM topics or JEL codes. These findings suggest that horizontal gender differences in thematic specialization, rather than bias in citation behavior, account for most of the observed citation gap. Our analysis highlights the importance of accounting for field heterogeneity when assessing academic recognition and contributes to ongoing discussions about fairness and diversity in economics publishing.

Keywords: Machine Learning; Gender Gaps; Structural Topic Model; Gendered Language; Research Fields.

JEL Classification: I20, J16, Z13.

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1 Introduction

During the past few decades, significant efforts have been made to improve gender representation in various fields, particularly in academia. However, despite these efforts, women remain underrepresented at the highest levels of the profession, including in prestigious economic journals and faculty positions. Gender disparities in academic publishing and career progression continue to be a pressing concern, especially in fields like economics, where such gaps can have long-lasting impacts on professional advancement and recognition.

In academia, promotions and career progression are heavily influenced by publications in the most prestigious journals, often referred to as the "Top 5" (American Economic Review, Quarterly Journal of Economics, Journal of Political Economy, Econometrica, and Review of Economic Studies). These journals set the benchmark for academic excellence and play a pivotal role in shaping research careers. A strong publication record in these journals is frequently regarded as a prerequisite for tenure, promotions, and broader academic recognition, making it crucial to examine gender disparities in this domain. Women are also underrepresented in Top 5 publications. In our sample, they are around 15% of the authors.

This contrasts with the findings of several academic studies that have documented persistent gender gaps in citations in economics. For instance, Card et al. (2020) found that women-authored papers in top economics journals receive more citations than men-authored papers with comparable referee scores, suggesting that women face higher publication standards. Similarly, Hengel and Moon (2023) extends this analysis, demonstrating that female-authored papers are cited 12 log points more than male-authored ones, with the citation premium rising to 20 log points when adjusting for the "*Matthew effect*"[1]. Other studies, such as Koffi (2021) and Ductor and Prummer (2024), highlight the importance of collaboration networks and research focus, showing that while women-authored papers receive a citation premium overall, this dynamic varies across subfields and journal prestige.

Taking citations as a proxy for quality, the gender citation gap raises the important question of whether women are held to higher standards in academic publishing. If female-

[1] The "*Matthew effect*"—a term coined by sociologist Robert K. Merton—refers to the phenomenon whereby well-known researchers or highly visible papers tend to accumulate more citations simply due to their existing prominence. In academic publishing, this creates a cumulative advantage, where recognition reinforces itself regardless of intrinsic quality (see (Merton, 1968)).

authored papers face stricter thresholds for acceptance, those published in the Top 5 journals should, on average, exhibit higher quality (more citations). However, citations are also influenced by the research agenda, as some fields attract more citations than others. Therefore, the key question is not simply whether female-authored papers are cited more, but whether they receive more citations after controlling for differences in research areas.

In this paper, we investigate whether gender disparities exist in citation patterns within the Top 5 economics journals. Using an extended dataset covering articles published from 1999 to 2023, we analyze whether female-authored papers are cited more frequently than male-authored ones, after controlling for research topics. We apply the same methodology introduced by Conde-Ruiz et al. (2022a), employing a Structural Topic Model (STM) to identify and control for latent research topics, allowing us to account for thematic differences across papers. Consistent with Conde-Ruiz et al. (2022a), we show that men and women exhibit different patterns when choosing research topics in economics. To measure citations, we complement the dataset with citation information from RePEc (Research Papers in Economics), a comprehensive database that tracks bibliographic data and citations for economics research. This addition enables us to systematically evaluate the impact of gender on citation patterns. Our results show that when controlling for research topics, the citation gaps between male- and female-authored papers narrow significantly, often becoming statistically insignificant. This indicates that the perceived citation disparity is closely tied to the thematic content and distribution of topics among authors, rather than systemic bias in how citations are allocated.

Similarly to us, Koffi (2021), Card et al. (2020), and Ductor and Prummer (2024), have also shown that the gender citation premium narrows when controlling for the JEL codes of the published articles. The Journal of Economic Literature (JEL) classification system has been widely used in the literature to capture field-level heterogeneity in the published papers to analyze the trends of the economic research[2], gender heterogeneity regarding the

[2]For example, Angrist et al. (2017) explore the classification of economics research by combining JEL codes with machine-learning techniques to examine long-term trends across fields and research styles, demonstrating how empirical work has gained prominence over time. Meanwhile, Kosnik (2014)leverages textual analysis on a large corpus of economics publications to document the stability and shifts in research focus across JEL categories over the past five decades, revealing a decline in macroeconomic research and an increasing emphasis on empirical methodologies.

research fields,[3] and also, as we have seen, the gender citation premium. We complement our analysis by replicating our machine learning exercise using JEL codes, and we will discuss the relationship between the two methodologies. For doing so, we enriched our dataset by incorporating the Journal of Economic Literature (JEL) codes assigned to each published article. These codes are taken from the metadata available in the RePEc database. When JEL codes were not listed in the published version, we retrieved them from the corresponding working paper version, if available. This step allowed us to systematically map each paper to one or more JEL categories and to compare these author-assigned classifications with the latent topics extracted through text analysis. We document persistent horizontal gender differences across primary JEL categories, confirming that men and women tend to specialize in different research fields. This horizontal differences seem to be very aligned with ones obtained with our STM approach [4]. In fact, we show that there is some relationship between estimated research topics and JEL codes, as well as in the allocation of papers across estimated research topics and JEL codes. By linking the two methodologies, we highlight their complementarities, and provide a more comprehensive characterization of research specialization across gender. After undertaking this complementarity analysis, we find that both methodologies have their advantages and limitations, but perform similarly well in addressing our research questions.

The structure of the paper is as follows. Section 2 describes the dataset and presents descriptive statistics on publication patterns, author gender composition, and citation trends across the Top 5 economics journals. Section 3 analyzes horizontal gender differences in research focus using two complementary approaches: a Structural Topic Model (STM) to estimate latent research topics from abstracts, and the Journal of Economic Literature (JEL) classification system. The section also discusses the limitations and advantages of JEL codes and explores the correspondence between both taxonomies. Section 4 examines gender disparities in citation outcomes, controlling for field specialization using both STM

[3] JEL codes have been used to highlight persistent gender differences in research fields. Lundberg and Stearns (2019) analyzes PhD dissertations in Economics from 1991 to 2017, using JEL codes to identify the research area. They find that women are more likely to focus on research fields as Labor and Public Economics than in Macro and Finance. Their results also show that this pattern has remained stable over time.

[4] Relatedly, Hospido and Sanz (2021) show that gender gaps in conference acceptance rates are larger in male-dominated fields like finance, yet field fixed effects do not fully account for these disparities.

topics and JEL codes, and assesses the extent to which topic composition and JEL codes explain the observed citation gap. Finally, Section 5 concludes and offers policy implications related to diversity and field representation in academic publishing.

2 Data: Articles, Journals, Authors and Citations

In this section, we analyze the publication patterns in the top five economics journals, focusing on the number of articles published, the gender composition of authorship teams, and the citations received per paper. We use a database similar to that employed by Conde-Ruiz et al. (2022a), which includes articles published in the Top 5 economics journals (American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, and Review of Economic Studies) in the period 2002-2019. However, for this article we extend the period of analysis to include all articles published from 1999 to 2023, which increases the number of observations from 5,311 articles in the original dataset to 7,244 articles in our updated version. Additionally, we complement this database with information on the citations received by each article, sourced from the RePEc (Research Papers in Economics) database. RePEc is a comprehensive database that aggregates bibliographic information on economics research, including article metadata, working papers, and citation counts. This extensive database covers virtually all relevant journals and a significant number of working papers (pre-prints) from various institutions, with more than 60,000 economists registered[5]. It allows us to track the impact of each article across a wide range of economics publications, providing a detailed picture of citation dynamics over time.

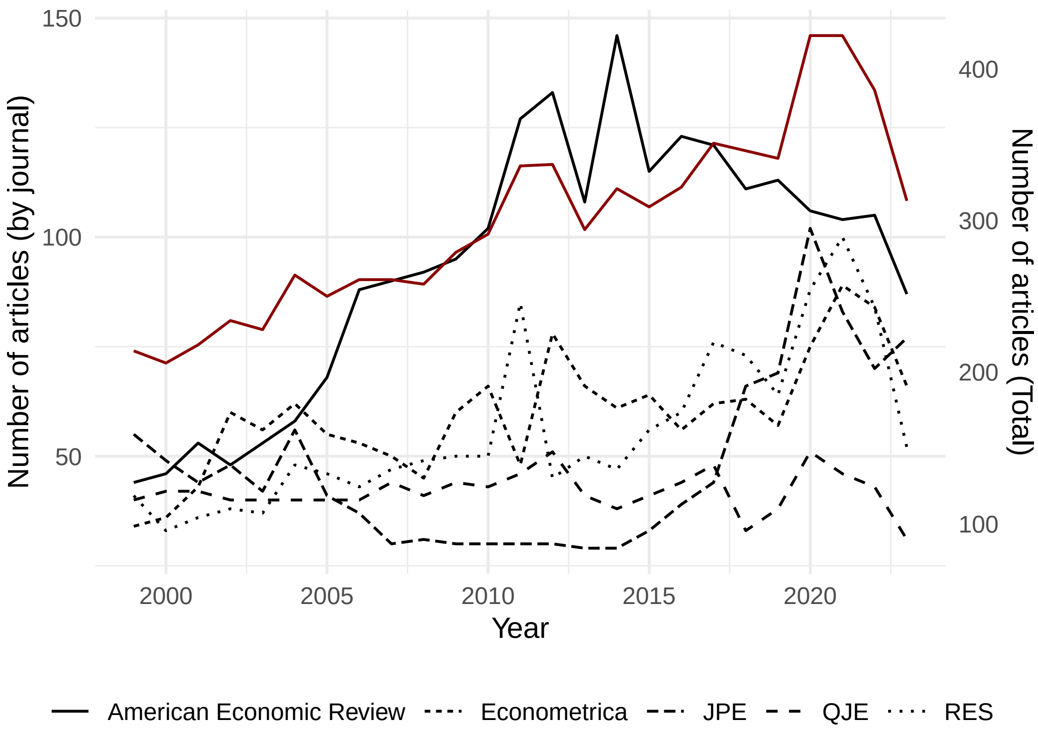
Figure 1 shows the number of articles published annually in the top five economics journals over time. The left axis displays the number of articles published per journal, while the right axis represents the total number of articles published across all five journals combined. The data reveals an upward trend in the total number of articles published until around 2015. Notably, the American Economic Review consistently publishes the highest number of articles, around 35-40% of total.

[5]For more details, see `http://repec.org/`. RePEc, dedicated to enhancing the dissemination of economic research, compiles metadata from over 2,000 publishers, encompassing academic and commercial publishing houses, research organizations, policy institutions, and think tanks. Additional applications of this data in economics are explored in Zimmermann (2013) and Cabrales et al. (2024)

Table 1 : Descriptive Statistics by Journal

	Total			By Article		
Journal	Articles	Authors	Female	Authors	Female	Citations by year
AER	2211	5,054	973	2.28	0.44	13.71
Econometrica	1,471	3,244	427	2.17	0.29	9.69
JPE	1,171	2,267	409	2.24	0.34	10.41
QJE	1,022	2,566	476	2.46	0.45	17.64
RES	1,369	3,068	506	2.19	0.36	7.53
Total	7244	16,663	2,793	2.26	0.37	11.75

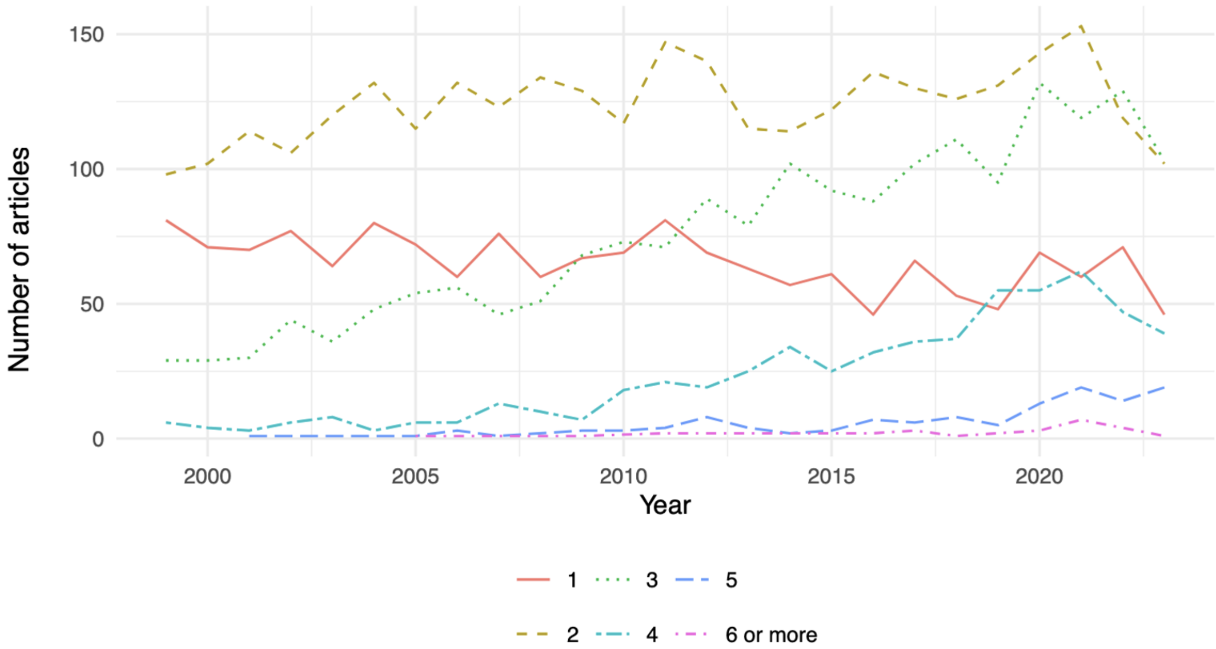
Figure 1 : Number of Articles Published per year in Top 5 Journals.



Note: Publications exclude notes (without abstract), comments, announcements, and Papers and Proceedings (P&P). Red line corresponds to the total number of articles.

Figure 2 reveals that articles with two authors consistently dominate the publications, maintaining the highest share throughout the time period. Articles authored by a single author exhibit a declining trend, indicating a shift away from solo-authored research over time. Articles with three and four authors have steadily increased, suggesting a growing trend toward collaborative work. Papers with five authors or six or more authors remain relatively rare but show a modest increase in recent years, reflecting a gradual rise in larger collaborative teams.

Figure 2 : Number of Articles Published per year in Top Journals by Number of Authors.

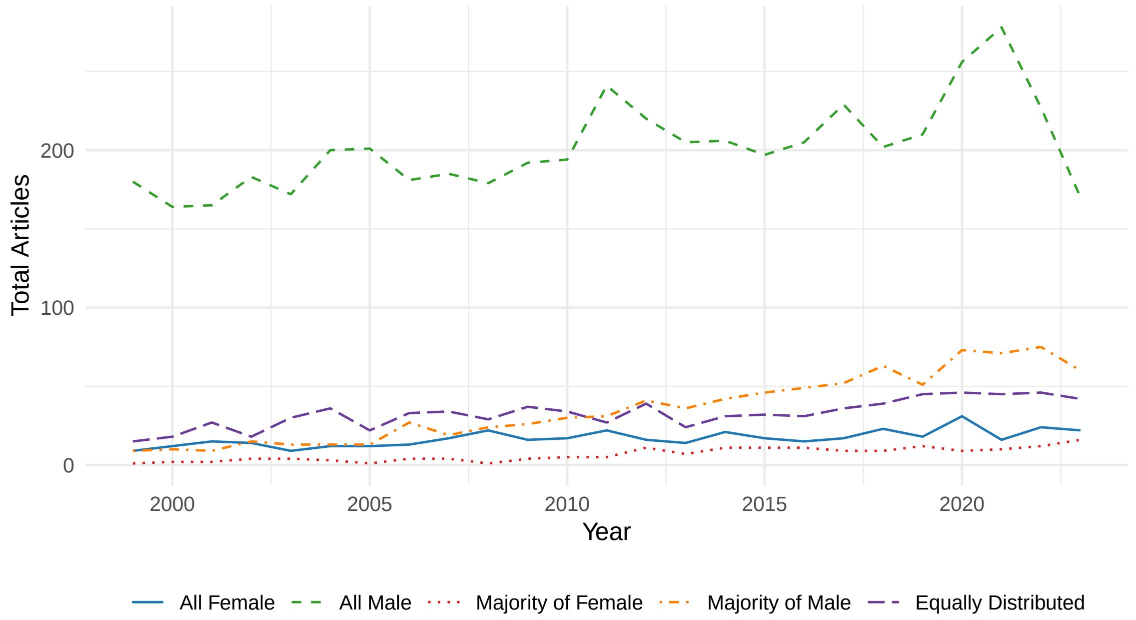


Note: Publications exclude notes (without abstract), comments, announcements, and Papers and Proceedings (P&P).

Figure 3 illustrates the number of articles published annually in Top 5 economics journals, categorized by the gender composition of authorship teams: All Female, All Male, Majority Female, Majority Male, and Equally Distributed. The figure shows that articles authored by all-male teams dominate throughout the period, maintaining the highest share of publications by a significant margin, though their numbers peak around 2021 and decline slightly thereafter. Teams with a majority of male authors consistently contribute the second-largest share of articles, showing a slight upward trend over time. Equally distributed teams exhibit a modest but steady increase in publications, reflecting a gradual shift toward more gender-balanced collaborations. In contrast, all-female teams and teams with a majority of female authors represent a much smaller share of publications, with limited growth over the years.

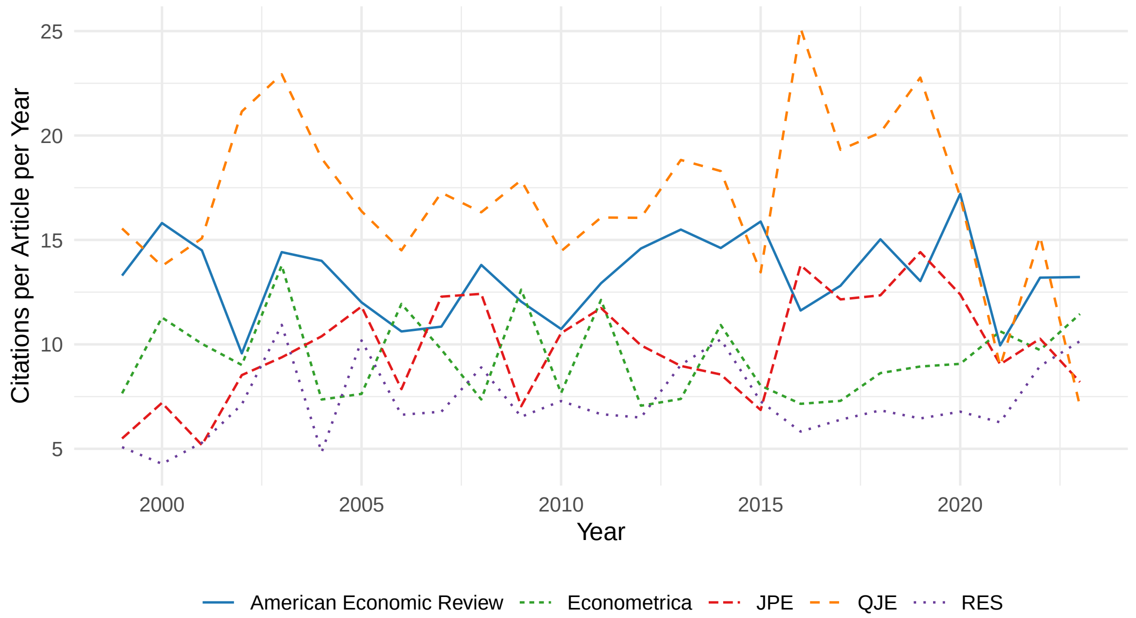
When analyzing annual citations per article in the top economics journals (Figure 4), clear differences emerge. The Quarterly Journal of Economics (QJE) consistently registers the highest average citation counts, with notable peaks in the early 2000s and around 2015, underscoring its influence. The American Economic Review (AER) maintains relatively

Figure 3 : Number of Articles per year in Top Journals by Gender Composition.



Note: Publications exclude notes (without abstract), comments, announcements, and Papers and Proceedings (P&P).

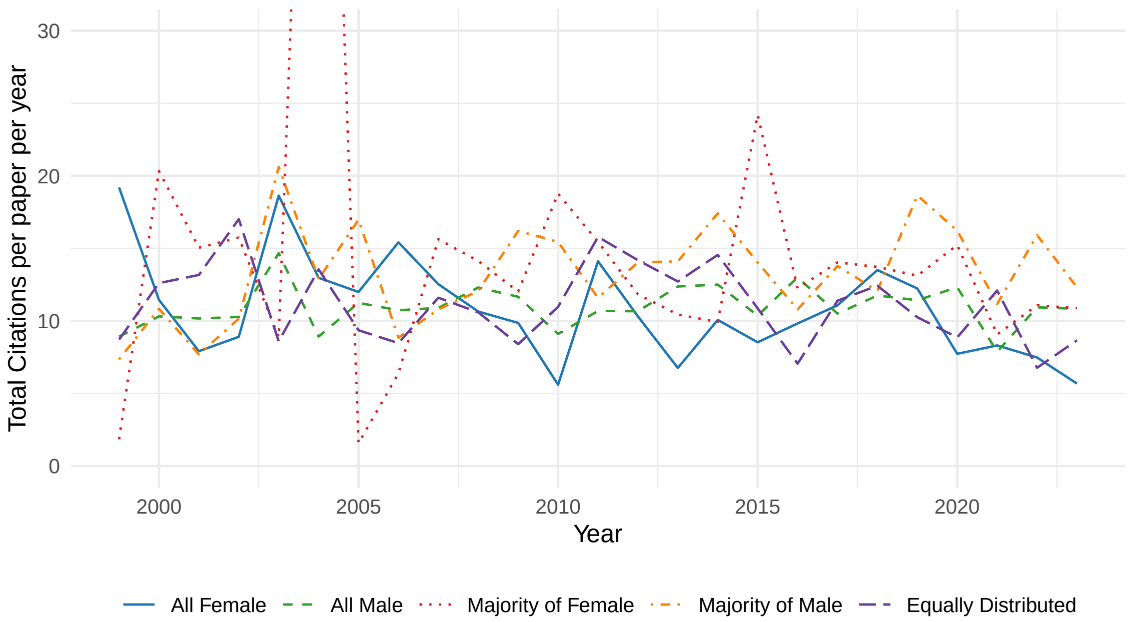
Figure 4 : Trends in Annual Citations per Article Across Leading Economics Journals.



Note: Publications exclude notes (without abstract), comments, announcements, and Papers and Proceedings (P&P).

high and stable citation levels over time, likely reflecting its broad readership. In contrast, Econometrica, the Journal of Political Economy (JPE), and the Review of Economic Studies (RES) show comparatively lower averages, with RES persistently garnering the fewest citations per article. These patterns highlight the varying scope, audience, and impact of each journal's publications.

Figure 5 : Annual Citations per article in Top Journals by Gender Composition of Authors.



Note: Publications exclude notes (without abstract), comments, announcements, and Papers and Proceedings (P&P).

Finally, Figure 5 illustrates the annual citations per article and per year in the Top economics journals, categorized by the gender composition of authorship teams: All Female, All Male, Majority Female, Majority Male, and Equally Distributed. The figure highlights that differences in citation patterns across gender compositions are relatively small. Most categories, including All Male, Equally Distributed, and Majority Male teams, follow similar trends with only slight variations over time.

Our analysis highlights persistent disparities in gender representation, with male-dominated teams consistently accounting for the largest share of publications, while female-dominated teams remain underrepresented. Additionally, differences in citation patterns emerge, with some variation across journals and gender composition, although these differences tend to be relatively small on a per-paper basis. These results provide a foundation for the subsequent sections, where we investigate the drivers of these disparities and explore potential mechanisms underlying the observed pattern.

3 Gender Horizontal Differences in Research

3.1 Gender Horizontal Differences in Latent Estimated Resarch Topics

As in Conde-Ruiz et al. (2022a) we use the Structural Topic Model (STM), developed by Roberts et al. (2019), to identify the research topics in our extended data based on the abstracts of articles published in top economics journals from 1999 to 2023. This method identifies latent topics in the text, offering a probabilistic, low-dimensional representation (topics) of high-dimensional data (abstracts) while preserving as much informational content as possible.[6]

Our dataset comprises 7,244 abstracts. After extracting the full set of words, we apply text cleaning procedures designed to reduce the vocabulary and emphasize terms with greater informational value. These steps include removing stop words, performing stemming, and filtering out infrequent terms. As a result, the initial vocabulary of 13,835 words shrinks to a more focused corpus of 4,241 unique terms[7]. These words were then organized into a document-term matrix, which served as the input for the STM algorithm. STM identifies k topics that best fit the document-term matrix where each topic is a probability distribution over words. Intuitively, certain words tend to appear more frequently in texts discussing specific topics than in others. An abstract (document) is treated as a collection of words, each with different probabilities of belonging to one or more latent topics. Using this probabilistic relationship between words and topics, the STM allocates each document d to the various topics by estimating a distribution θ_d.

[6]Compared to the baseline Latent Dirichlet Allocation (LDA), STM improves the estimation by incorporating covariates such as publication year and journal name. LDA is the foundational algorithm for topic modeling and one of the most widely used machine learning methods for reducing the dimensionality of textual data. For a technical overview of LDA, see Blei et al. (2003). Furthermore, Hansen et al. (2017), Bansak et al. (2024) and Beneito et al. (2021) provide examples of its application in economic research.

[7]Our cleaning process of the text is as follows: We have converted all text to lowercase. We have removed common stop words (e.g., "for," "in") based on the SMART list developed at Cornell University, which is widely used in text analysis to exclude non-informative words. We have also reduced words to their linguistic roots (e.g., "educ" instead of "education". Finally, we have eliminated terms that appear only once or twice in the entire dataset. We have followed the same preprocessing steps than in Conde-Ruiz et al. (2022a). See this article for more technical details.

3.1.1 Estimation of the Structural Topic Model (STM)

The first step of the estimation is to determine the number of topics k that best fits our text data. The optimal number of topics, k, in topic modeling using the Structural Topic Model (STM), represents the number of distinct latent topics that best balance statistical fit and interpretability. Each topic corresponds to a cluster of frequently co-occurring words that capture thematic patterns in the dataset, such as research fields or methodologies in a set of academic abstracts. Determining the optimal k ensures that the model identifies meaningful and manageable topics without being overly broad or fragmented.

In line with Conde-Ruiz et al. (2022a), we aim to identify the optimal number of topics for our analysis using Structural Topic Models (STM). Determining the appropriate number of topics is a critical step in STM applications, as it directly influences the interpretability and robustness of the resulting topics. Choosing too few topics may oversimplify the underlying thematic structure, while too many topics can lead to over-fragmentation and reduced clarity, ultimately hindering the usefulness of the model in deriving meaningful insights.

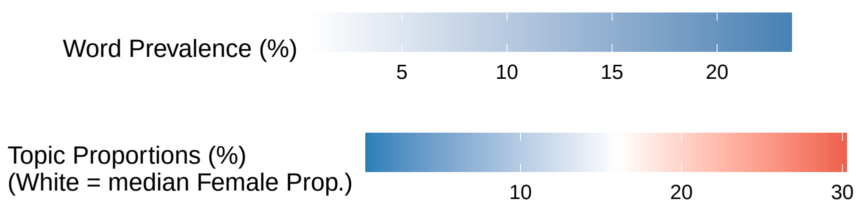
To identify the optimal number of topics (k), we estimate STM models with k ranging from 15 to 65 and assess their performance using held-out likelihood. The held-out likelihood provides a measure of the model's ability to generalize to unseen data by partitioning the dataset into training and test sets. Specifically, the model is trained on a subset of the data, and the likelihood of the held-out portion is evaluated based on the inferred topic-word distributions and document-topic proportions. A higher held-out likelihood indicates that the model captures the data's underlying structure effectively without overfitting. Our analysis shows that the held-out likelihood achieves its maximum value between $k = 49$ and $k = 60$, indicating that this range provides the best statistical fit.

In addition to held-out likelihood, we evaluate the quality of the topics using two complementary metrics: *exclusivity* and *semantic coherence*. Exclusivity measures the uniqueness of the words associated with each topic, ensuring that the top words in a topic are not frequently shared with other topics. This enhances the interpretability of the model by ensuring the distinctiveness of topics. Semantic coherence assesses the co-occurrence of the top words in each topic within the original documents, with higher coherence indicating that the topics are more meaningful and contextually grounded.

Balancing these metrics, we select $k = 50$ as the optimal number of topics. This choice reflects a trade-off between statistical fit, as indicated by the held-out likelihood, and interpretability, guided by the exclusivity and coherence metrics. By selecting $k = 50$, we achieve a parsimonious model that captures the thematic diversity of the data while maintaining the clarity and interpretability of individual topics. This approach aligns with best practices in the application of STM, ensuring that the model provides both robust quantitative results and actionable qualitative insights.

Figure 6 : Optimal K Topics Ranked by Prevalence in the Corpus ($k = 50$).

													Topic Prop.	Female Prop.
Topic 13	estim	variabl	function	method	condit	use	identif	data	paramet	distribut	structur	consist	5%	15.7%
Topic 47	prefer	choic	util	set	function	decis	expect	character	probabl	individu	rule	altern	3.5%	11.6%
Topic 42	test	statist	paramet	distribut	asymptot	infer	method	sampl	set	base	confid	condit	3.4%	14.5%
Topic 34	product	technolog	sector	industri	output	chang	input	labor	skill	increas	differ	plant	3.1%	16.6%
Topic 8	game	equilibrium	player	equilibria	strategi	payoff	play	perfect	exist	set	nash	repeat	3%	10%
Topic 22	wage	worker	employ	labor	job	earn	skill	market	increas	work	labour	occup	2.9%	18.1%
Topic 12	market	price	consum	competit	qualiti	equilibrium	demand	seller	trade	good	buyer	trader	2.8%	15.5%
Topic 21	percent	estim	hous	increas	year	use	data	demand	consum	averag	time	measur	2.8%	17.2%
Topic 32	experi	choic	subject	treatment	decis	experiment	random	predict	effect	control	make	field	2.7%	17.4%
Topic 15	shock	return	aggreg	volatil	stock	busi	cycl	fluctuat	time	dynam	real	money	2.7%	14.9%
Topic 41	firm	product	profit	entri	export	cost	industri	data	market	use	level	higher	2.6%	19.2%
Topic 35	trade	countri	intern	world	global	import	tariff	domest	develop	good	export	predict	2.5%	15.7%
Topic 5	agent	contract	commit	princip	optim	hazard	incent	moral	problem	incomplet	time	complet	2.4%	13.2%
Topic 38	polici	monetari	rate	inflat	interest	nomin	economi	effect	new	respons	expect	stabil	2.4%	14.5%
Topic 48	invest	financi	asset	liquid	financ	investor	capit	constraint	equiti	valu	cash	flow	2.4%	16.4%
Topic 16	children	parent	famili	child	marriag	crime	educ	increas	women	effect	birth	rate	2.3%	29.7%
Topic 3	inform	learn	signal	privat	agent	belief	asymmetr	structur	observ	aggreg	character	condit	2.3%	14.5%
Topic 10	optim	type	bargain	valu	problem	offer	implement	maxim	surplus	delay	case	suffici	2.2%	12.1%
Topic 4	school	student	colleg	effect	score	educ	high	test	teacher	peer	program	increas	2.2%	19.6%
Topic 11	behavior	individu	peopl	self	evid	differ	theori	trust	group	social	refer	ident	2.1%	19.9%
Topic 31	growth	citi	distribut	popul	locat	size	develop	local	spatial	law	across	region	2.1%	15.1%
Topic 29	cost	welfar	benefit	public	gain	privat	polici	reduc	increas	loss	good	improv	2.1%	16.1%
Topic 20	effect	immigr	innov	increas	local	patent	migrat	impact	exploit	state	exposur	causal	2.1%	22.5%
Topic 18	price	rate	exchang	currenc	adjust	cost	retail	chang	relat	quantiti	import	larg	2%	18.7%
Topic 45	polit	govern	institut	parti	polici	public	politician	support	democraci	elect	regim	legisl	2%	15.8%
Topic 14	consump	household	save	incom	life	age	cycl	wealth	individu	account	data	time	1.9%	18.6%
Topic 25	tax	incom	reform	optim	margin	rate	elast	taxat	wealth	increas	top	inequ	1.8%	16.8%
Topic 1	econom	empir	forecast	theoret	use	research	correct	predict	framework	develop	name	studi	1.8%	13.7%
Topic 27	risk	asset	avers	uncertainti	ambigu	portfolio	expect	premium	riski	share	util	loss	1.8%	14%
Topic 43	insur	program	health	care	plan	mortal	increas	drug	transfer	medic	reduc	provid	1.8%	24.6%
Topic 49	capit	human	educ	inequ	mobil	centuri	accumul	incom	state	econom	develop	return	1.7%	14.3%
Topic 39	match	alloc	stabl	substitut	agent	condit	exist	effici	equilibrium	market	side	constraint	1.7%	14.2%
Topic 19	debt	govern	default	borrow	credit	rate	bond	loan	interest	fiscal	mortgag	matur	1.6%	16.2%
Topic 9	auction	bid	valu	price	bidder	buyer	seller	revenu	privat	first	effici	common	1.5%	14.3%
Topic 6	long	bank	run	short	term	credit	lend	fund	effect	deposit	central	loan	1.5%	15.3%
Topic 23	women	gap	gender	black	men	white	femal	ethnic	racial	differ	race	male	1.5%	30.2%
Topic 44	perform	manag	organ	task	promot	decis	monitor	abil	incent	compens	better	pay	1.4%	19.7%
Topic 17	social	incent	effici	communiti	coordin	individu	group	arrang	achiev	generat	societi	outcom	1.4%	18.5%
Topic 33	regul	hospit	enforc	pollut	patient	emiss	air	estim	cost	qualiti	energi	increas	1.4%	19.7%
Topic 30	group	member	bias	rule	decis	news	polici	media	major	voter	make	expert	1.4%	18.6%
Topic 36	action	observ	state	time	belief	cost	choos	attent	payoff	process	signal	game	1.3%	12.1%
Topic 40	resourc	agricultur	land	properti	ownership	right	farmer	rural	water	villag	develop	increas	1.3%	21.6%
Topic 46	network	connect	interact	link	equilibrium	format	structur	dynam	cluster	form	central	diffus	1.2%	17.4%
Topic 2	communic	strateg	multipl	adapt	complementar	self	equilibrium	sender	lie	climat	messag	persuas	1.1%	14.1%
Topic 24	mechan	exchang	design	compat	donor	give	market	prioriti	particip	new	patient	assign	1.1%	14.6%
Topic 7	search	unemploy	friction	job	durat	time	rate	benefit	internet	cost	data	depend	1%	14.7%
Topic 26	vote	elect	voter	advertis	candid	union	campaign	strateg	turnout	share	outcom	state	1%	14.5%
Topic 28	power	extrem	merger	increas	group	grant	right	religi	violenc	chang	conflict	consolid	0.9%	16.5%
Topic 37	effort	innov	team	success	contest	prize	competit	win	winner	compet	one	outcom	0.8%	16%
Topic 50	studi	use	data	one	import	analysi	respons	induc	market	increas	heterogen	develop	0.4%	17.3%



Note:The first numerical column shows the topic's share in the overall corpus (i.e., its prevalence across all abstracts). The second column reports the proportion of female-authored papers associated with each topic. Topics are ordered by prevalence. Color shading reflects the share of female authorship: darker shades indicate higher female representation relative to the median across topics.

Figure 6 displays the keywords associated with each of the 50 latent topics identified using the Structural Topic Model. The words within each row are arranged from left to right based on their probability of appearing in each topic. To facilitate the interpretation of the latent topics, Table 2 assigns each topic a corresponding JEL code. For this exercise, we have employed ChatGPT (OpenAI, 2024) that has analyzed the top-ranked keywords associated with each topic and proposed the most semantically appropriate JEL code.

Topic & Keywords	**JEL Code and Description (ChatGPT)**
Topic 13: *estim, variabl, function, method, condit, use, identif*	C10 – General Mathematical and Quantitative Methods
Topic 47: *prefer, choice, util, set, function, decis, expect*	D81 – Criteria for Decision-Making under Risk and Uncertainty
Topic 42: *test, statist, paramet, distribut, asymptot, infer*	C12 – Hypothesis Testing: General
Topic 34: *product, technolog, sector, industri, output, chang*	O33 – Technological Change: Choices and Consequences
Topic 8: *game, equilibri, player, strategi, payoff*	C72 – Noncooperative Games
Topic 22: *wage, worker, employ, labor, job, earn*	J31 – Wage Level and Structure; Wage Differentials
Topic 12: *market, price, consum, competit, equilibri*	D40 – Market Structure and Pricing
Topic 21: *percent, estim, hous, increas, year, use, data*	R21 – Housing Demand
Topic 32: *experi, choic, subject, treatment, decis*	C91 – Laboratory, Individual Behavior
Topic 15: *shock, return, aggreg, volatil, stock, busi*	G12 – Asset Pricing
Topic 41: *firm, product, profit, entri, export, cost, industri*	L10 – General: Industrial Organization
Topic 11: *behavior, individu, peopl, self, evid, differ*	D91 – Intertemporal Household Choice; Life Cycle Models
Topic 4: *school, student, colleg, effect, score, educ, high*	I21 – Analysis of Education
Topic 5: *agent, contract, commit, princip, optim, hazard*	D86 – Economics of Contract: Theory
Topic 38: *polici, monetari, rate, inflat, interest, nnom*	E52 – Monetary Policy
Topic 48: *invest, financi, asset, liquid, finance, investor*	G11 – Portfolio Choice; Investment Decisions
Topic 16: *children, parent, famili, child, marriag, crime*	J13 – Fertility; Family Planning; Child Care; Children
Topic 3: *inform, learn, signal, privat, agent, belief*	D82 – Asymmetric and Private Information
Topic 10: *optim, type, bargain, valu, problem, offer*	C78 – Bargaining Theory; Matching Theory
Topic 20: *effect, immigr, innov, increas, local, patent*	O31 – Innovation and Invention: Processes and Incentives
Topic 31: *growth, citi, distribut, popul, local, size*	R11 – Regional Economic Activity
Topic 9: *auction, bid, valu, price, bidder, buyer*	D44 – Auctions
Topic 25: *tax, incom, reform, optim, margin, rate*	H21 – Taxation and Subsidies: Efficiency; Incidence
Topic 18: *price, rate, exchang, currenc, adjust*	F31 – Foreign Exchange
Topic 45: *polit, govern, institut, parti, polici*	H11 – Structure, Scope, and Performance of Government
Topic 14: *consum, household, save, incom, life, cycl*	D14 – Household Saving; Personal Finance
Topic 26: *econom, emperi, forecast, theoret, use*	C53 – Forecasting and Prediction Methods
Topic 1: *econom, emperi, forecast, theoret, use*	B41 – Economic Methodology
Topic 27: *risk, asset, avers, uncertain, ambigu*	G32 – Financing Policy; Financial Risk and Risk Management
Topic 43: *insur, program, health, care, plan, mortal*	I13 – Health Insurance, Public and Private
Topic 49: *capit, human, health, care, plan, mortal*	I15 – Health and Economic Development
Topic 39: *match, alloc, stabl, substitut, agent, condit*	C78 – Bargaining Theory; Matching Theory
Topic 19: *debt, govern, default, borrow, credit, rate*	H63 – Debt; Debt Management
Topic 6: *long, bank, run, short, term, credit*	G21 – Banks; Other Depository Institutions
Topic 23: *women, gap, gender, black, men, white*	J16 – Economics of Gender; Non-labor Discrimination
Topic 44: *perform, manag, organ, task, monitor, decis*	M52 – Personnel Economics: Compensation and Compensation Methods
Topic 17: *social, incentiv, effect, communiti, coordin*	Z13 – Social Norms and Social Capital
Topic 30: *group, member, bias, rule, decis, news*	D91 – Behavioral Economics
Topic 36: *action, observ, state, time, belief, choos*	D83 – Search; Learning; Information and Knowledge
Topic 40: *resourc, agricultur, land, properti, right*	Q15 – Land Ownership and Tenure; Land Reform

Table 2 : Suggested JEL Codes for Latent Topics (Compact Landscape Format)

However, assigning labels to the estimated latent topics based on commonly recognized fields in Economics is not the primary goal of the analysis. Instead, latent topics may capture a broader range of dimensions, including not only research fields but also methodologies or writing styles, offering a more comprehensive understanding of the structure and diversity within the dataset.

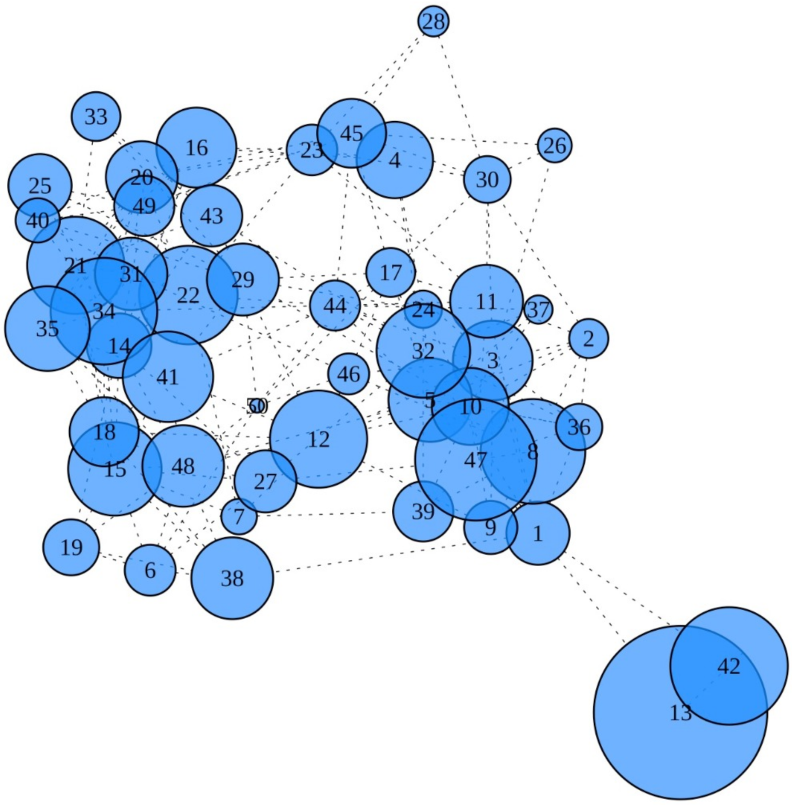
Once we have identified the estimated latent topics, we can analyze how our documents/abstracts are distributed among them. In allocating an abstract to a particular topic we consider our underlying θ_d distribution.

Figure 7 represents the network of latent topics, illustrating the connections across the identified topics. Each circle represents a latent topic, and its size reflects the proportion of documents associated with that topic. The connections between topics indicate their semantic similarity, meaning that topics that are connected share overlapping keywords and are more likely to co-occur within the same documents. Topics that are positioned closer together in the figure are more semantically related, often representing similar research fields, methodologies, or writing styles (see, for example, that topics 16, 43 and 23 are connected).

Figure 8 represents the network of latent topics for female-authored papers, which shows the gender-specific distribution across the identified topics. Similar to Figure 7, each circle represents a latent topic, and its size reflects the proportion of all female-authored documents associated with that topic. Significant differences are observed between the two network figures. This is primarily because women account for less than 20% of the authors in the sample, and also because distinct gender-specific patterns exist regarding research topics. However, this latter aspect is better visualized through the conditional distributions of research topics by gender.

Figure 9 shows the empirical density distributions of topics across male and female authors, conditional on having published a paper in a Top 5 economics journal. These distributions reflect the probability that a paper written by a male or female author belongs to one of the 50 latent topics identified through the Structural Topic Model (STM). Figure 9 highlights significant "horizontal" differences in research focus between male and female authors, as evidenced by the empirical density distributions of topics. The figure shows that male and female authors are not evenly distributed across the 50 latent topics, with certain areas displaying pronounced gender disparities or important "horizontal" differences.

Figure 7 : Topic Connectedness and Authorship Distribution.



The horizontal differences in research between men and women are best observed by subtracting these two conditional distributions, as illustrated in Figure 13.

Women show a relatively higher propensity than men to make research on topics with positive mass. This analysis leads us to identify topics 23 and 16 as those where, in relative terms, women are more likely to engage, while topic 8 exhibits a similar pattern for men.[8]

[8]Alternatively, instead of analyzing the difference in topic mass between the conditional distributions,

Figure 8 : Topic Connectedness and Female Authorship Distribution.

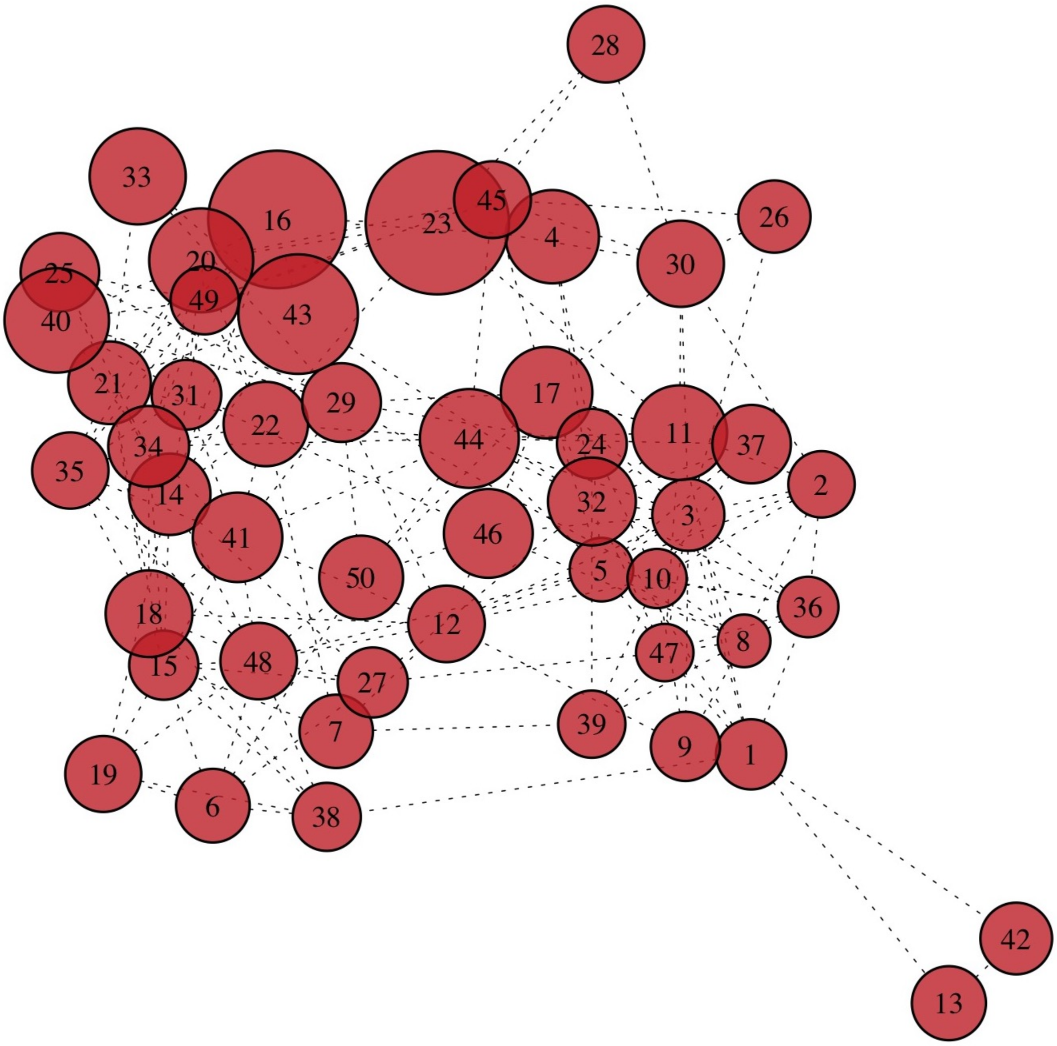
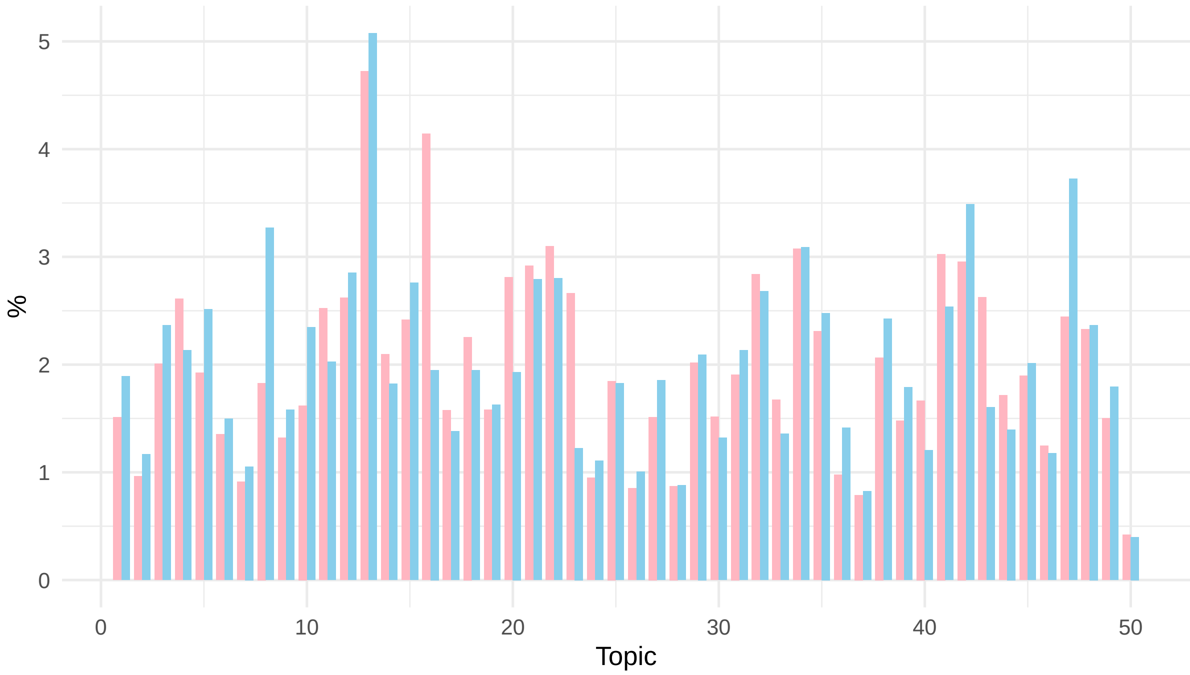


Figure 11 illustrates the content of these latent topics 23 y 16 with the typical Word Cloud graph. Based on the keywords in each topic, we can infer their associated fields of research. Topic 23 (Panel (a)) appears to relate to gender studies, racial discrimination, and social inequality, as indicated by words such as "women," "gender," "racial," "discrimination," "black," and "white." This suggests a focus on labor economics, public policy, and studies on diversity and inclusion. Topic 16 (Panel (b)) seems to correspond to family economics and

$Pr(t|f) - Pr(t|m)$, we could have examined the ratio $\frac{Pr(t|f)}{Pr(t|m)}$, which, in this particular case, would have led to the same conclusions regarding the topics that are relatively more prevalent. This approach of analyzing ratios to identify the most distinctive characteristic that separates one group from another was proposed by Bordalo et al. (2016) as a formalization of the concept of stereotype originally introduced by Kahneman and Tversky.

Figure 9 : Empirical distributions across topics between males and females (conditional on having published an article in Top 5).

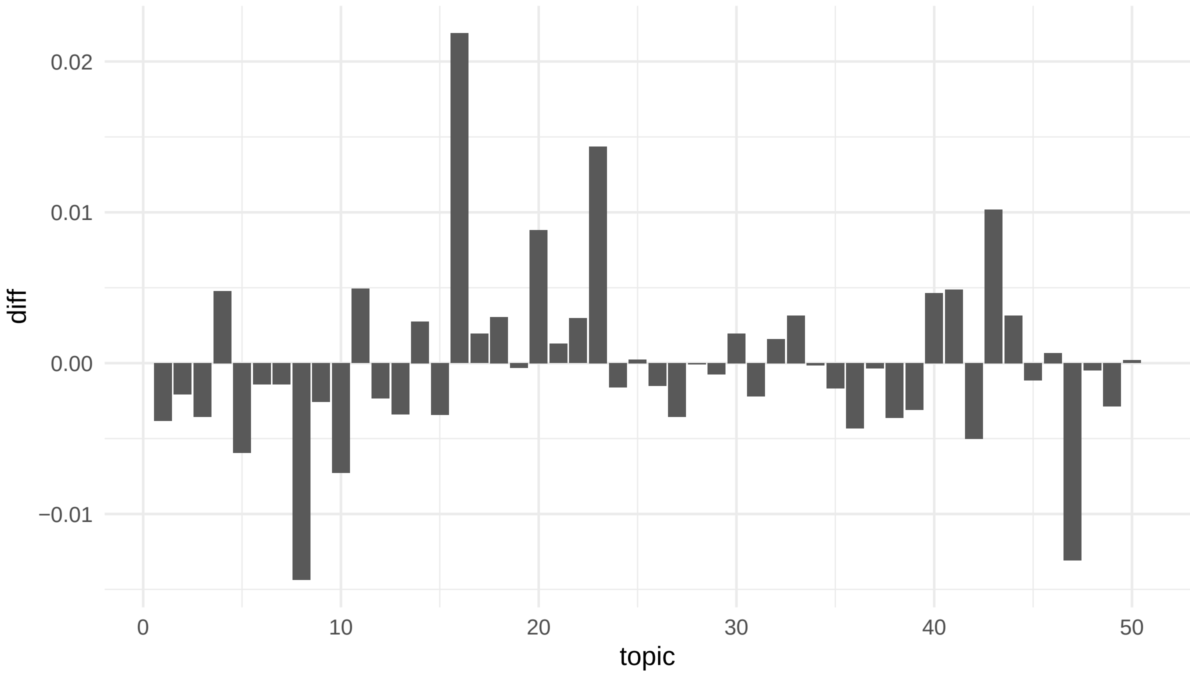


Note: This figure shows the empirical distribution of estimated research topics by gender, conditional on having published in a Top 5 economics journal. Each bar represents the percentage of articles by male (blue) and female (pink) authors assigned to each of the 50 STM-estimated topics.

child welfare, with words like "children," "family," "parent," "marriage," "education," and "birth," pointing to research areas such as family dynamics, the effects of marriage, child development, and access to education, likely within development economics, social policy, and education economics. These topics highlight applied areas of research where female authors are more represented.

Similarly, Topic 8 plays the same role for men. Figure 17) shows the word cloud for Topic 8, which has the highest difference of conditional probability between the males and females, $Pr(t|m) - Pr(t|f)$. The most prominent terms, such as "equilibrium," "game," "strategy," "player," and "payoff," indicate that this topic is centered on game theory and related areas in economic theory. The presence of terms like "Nash," "equilibria," "stochastic," and "dynamic" suggests a focus on strategic behavior, repeated games, and mathematical modeling.

Figure 10 : Difference between the Empirical distributions across topics between females and males (conditional of having published an article in Top 5).



3.2 Correspondence between Estimated Latent Research Topics and JEL codes

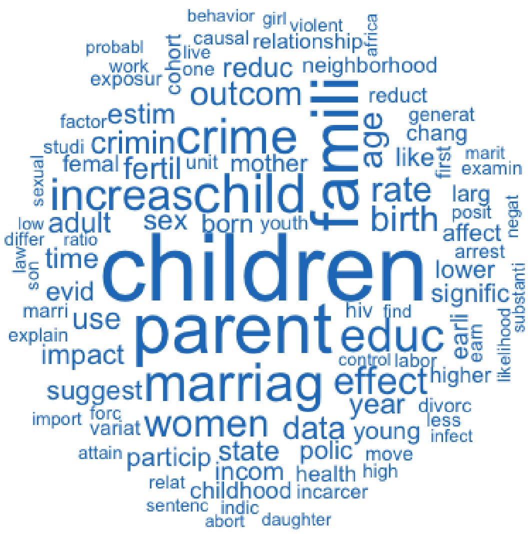
Having established the presence of horizontal differences in research focus through the estimation of latent topics, this section examines how these topics relate to the Journal of Economic Literature (JEL) classification system. The JEL system is a standardized taxonomy developed by the American Economic Association (AEA) to categorize economic research based on its thematic focus. It consists of 20 primary categories, each representing a broad field of economics. Within these, there are 146 secondary categories, which further refine the classification into specific research areas. Additionally, the system includes 856 tertiary categories, providing a granular breakdown of subfields within each secondary classification. This hierarchical structure allows for a systematic organization of economic research, facilitating literature searches, enhancing comparability across studies, and enabling a more detailed analysis of research trends and academic contributions. Given its widespread use in top-tier economics journals, the JEL classification system provides a valuable framework for examining potential horizontal differences in research focus across gender lines.[9]

[9] The classification of economic research through Journal of Economic Literature (JEL) codes has been extensively analyzed in the literature, highlighting its historical evolution, methodological implications,

Figure 11 : Topic Word Clouds of Topic 23 and Topic 16. These are the topics with the highest and second-highest difference of conditional probabilities between females and males, $Pr(t|f) - Pr(t|m)$.

(a) Topic 23.

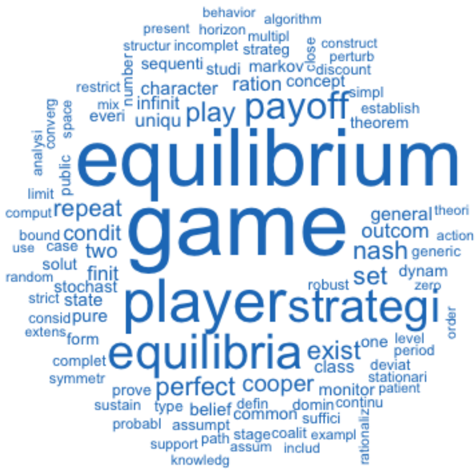
(b) Topic 16.



To begin our analysis, we focus on horizontal differences using the primary JEL categories, which represent broad research fields in economics. First, we examine the overall distribution of papers across these primary fields, identifying the number of publications within each category. Next, we assess the gender composition of each field by calculating

and role in shaping the discipline. Cherrier (2017) and Cherrier (2015) provide a comprehensive historical account of the JEL classification system, emphasizing how its revisions reflect deeper debates about the boundaries between theoretical and applied economics, as well as the structuring of economic knowledge.

Figure 12 : Topic 8 (topic with the highest difference of conditional probabilities between males and females, $Pr(t|m) - Pr(t|f)$).



the proportion of female-authored papers, providing a preliminary view of gender disparities in research focus. Finally, we analyze the conditional distributions by gender, determining how male and female authors allocate their research efforts across different fields.

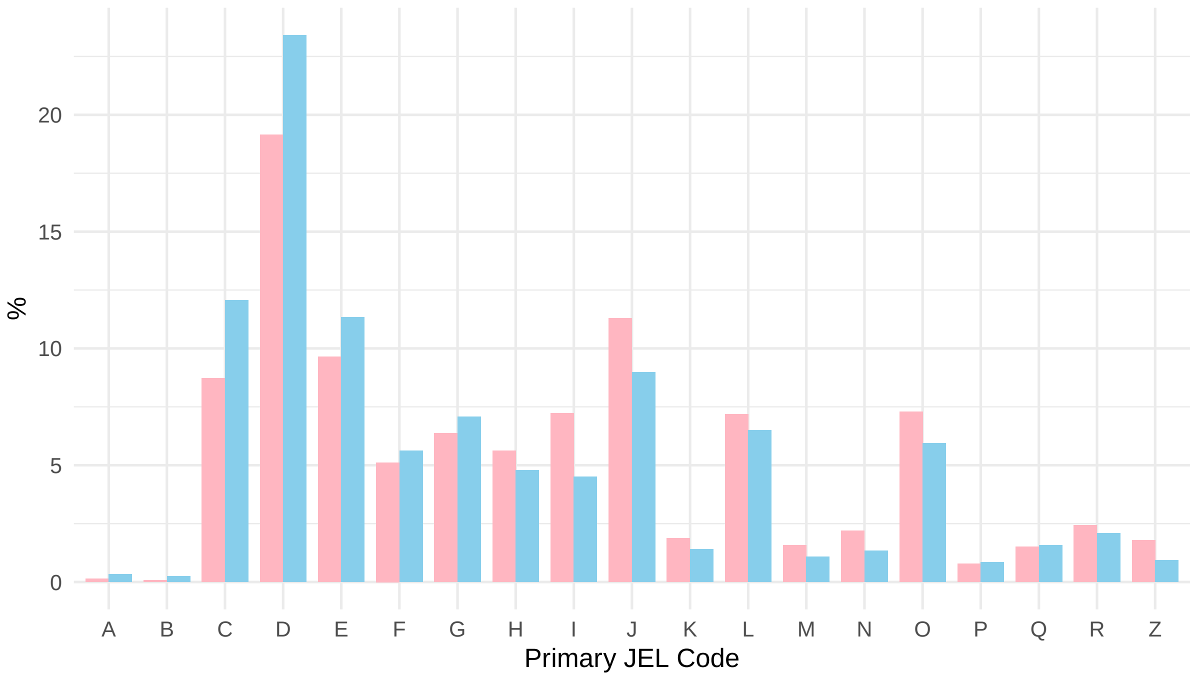
Table 3 presents the distribution of papers and authors across primary JEL codes, along with the percentage of female authors in each category. The data reveal significant heterogeneity in research output and gender representation across fields. Notably, Macroeconomics and Monetary Economics (E) and Mathematical and Quantitative Methods (C) account for a substantial share of publications, yet exhibit relatively low female representation. In contrast, fields such as Health, Education, and Welfare (I) and Labor and Demographic Economics (J) show a higher proportion of female authors, consistent with prior findings on gender disparities in economics research.

Table 3 : Percentage of Authors and Papers per Primary JEL Code

JEL	Name	Papers	Authors	Female
A	General Economics and Teaching	0.30	0.28	0.15
B	History of Economic Thought, Methodology, and Heterodox Approaches	0.21	0.15	0.08
C	Mathematical and Quantitative Methods	11.49	11.40	8.73
D	Microeconomics	22.68	22.59	19.14
E	Macroeconomics and Monetary Economics	11.05	10.71	9.65
F	International Economics	5.53	5.29	5.12
G	Financial Economics	6.96	6.92	6.37
H	Public Economics	4.93	5.02	5.62
I	Health, Education, and Welfare	4.97	5.44	7.23
J	Labor and Demographic Economics	9.37	9.73	11.29
K	Law and Economics	1.48	1.42	1.88
L	Industrial Organization	6.62	6.31	7.18
M	Business Administration and Business Economics, Marketing, Accounting, Personnel Economics	1.16	1.22	1.58
N	Economic History	1.49	1.44	2.20
O	Economic Development, Innovation, Technological Change, and Growth	6.16	6.24	7.28
P	Political Economy and Comparative Economic Systems	0.83	1.01	0.78
Q	Agricultural and Natural Resource Economics, Environmental and Ecological Economics	1.57	1.52	1.51
R	Urban, Rural, Regional, Real Estate, and Transportation Economics	2.15	2.23	2.43
Y	Miscellaneous Categories	-	-	-
Z	Other Research Fields	1.07	1.09	1.78

Figure 13 (similar to Figure 9 done with latent topics) illustrates the empirical distribution of male and female authors across primary JEL codes, conditional on having published in a Top 5 economics journal. The figure reveals notable horizontal differences in research specialization by gender. Male authors (blue bars) are disproportionately concentrated in Microeconomics (D), which exhibits the highest gender gap, as well as in Macroeconomics and Monetary Economics (E) and in Mathematical and Quantitative Methods (C). In contrast, female authors (pink bars) are more prevalent in Health, Education, and Welfare (I) and Labor and Demographic Economics (J). These patterns align with prior evidence on the gendered division of research fields, where women tend to be more represented in applied microeconomics areas, while men dominate in more theoretical and quantitatively intensive fields.

Figure 13 : Empirical distributions across Primary JEL codes between males and females (conditional on having published an article in Top 5).



Similarly to Figure 13, Figures A 1 and A 2 in the Appendix display the difference in empirical distributions across primary JEL codes (one-digit level), comparing male and female authors conditional on having published in a Top 5 economics journal. Positive values indicate research fields where female are relatively overrepresented (in the conditional distribution), while negative values correspond to fields with a higher proportion of male authors.

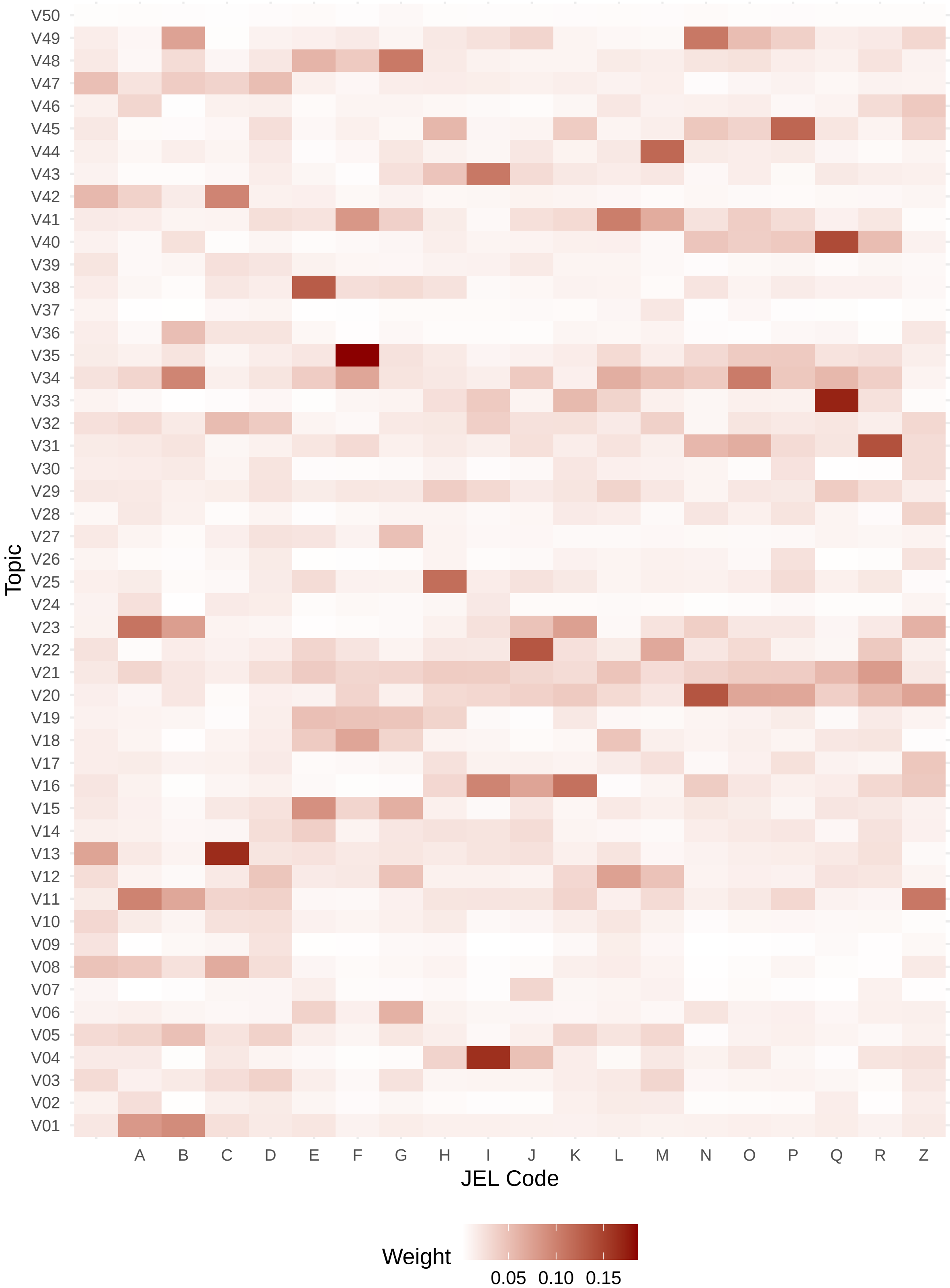
The results reveal pronounced horizontal segregation across research specializations. Men are more prevalent in aproximately 50% of the secondary JEL codes and women in the other 50%. J1 and D8 are the JEL codes that, in relative terms, are most frequently used by female and male, respectively. The JEL code J1 falls under Demographic Economics. More specifically, it covers research fields like fertility, family planning, child care, children, and youth. On the other hand, JEL code D8 refers to topics related to Information, Knowledge, and Uncertainty. This broad category includes sub-categories like decision-making under risk and uncertainty, asymmetric information, search and learning. Notice that the JEL codes most representative of men and women exhibit a pattern similar to the most representative latent topics discussed earlier, where women appear relatively more inclined toward applied research, while men tend to focus more on theoretical work. This seems to suggest that there is a relationship between the latent topics estimated from text analysis and the JEL codes assigned to papers.

To visualize the relationships between topics and JEL codes, we plot a correlation heatmap with rows as topics and columns as JEL codes, thereby identifying which topics appear most prominently under certain JEL codes.[10] In particular, Figure 14 shows how STM-derived topics (rows) map onto 0-digit JEL codes (columns). Each cell in the heatmap represents the weight of a given topic for a particular JEL code, with darker shades indicating stronger associations. The distribution reveals a clear many-to-many relationship: most JEL codes are composed of multiple topics, and conversely, many topics contribute to more than one JEL category. Some topics exhibit sharp concentration around specific JEL codes—such as V35 with code D (Microeconomics), V14 with code B (History of Economic Thought), and V06 with code H (Public Economics)—suggesting a high degree of topical coherence in those cases. In contrast, other topics, such as V02 or V39, are more diffusely distributed across multiple JEL codes, indicating broader thematic overlap. This visualization highlights both the granularity and complementarity between the latent topics inferred from textual content and the standardized classification provided by the JEL taxonomy.[11]

[10]In the the Appendix, we theoretically explain how this correlation heatmap is built to capture the relationships between STM topics and JEL codes.

[11]Appendix Figure 3 replicates this analysis using the 1-digit JEL classification. At this higher level of disaggregation, the mapping between topics and JEL codes becomes notably noisier, with few strong, isolated correspondences. The figure suggests that many topics span across multiple subfields within broader categories (e.g., C2, D8, E3), and that the 1-digit JEL taxonomy may obscure rather than reveal the topical

Figure 14 : Correspondences between JEL Codes (0-Digit) and Topics.



focus of many papers.

3.2.1 Advantages and Limitations of Estimated Latent Research Topics and JEL Codes

We find that both latent topics estimated through text analysis and JEL codes assigned to papers are useful for capturing horizontal gender differences in economic research. Each methodological approach has its own advantages and limitations, and their suitability depends on the specific application. For example, the mapping between texts and latent topics is fully automated, whereas the JEL classification system relies on self-assignment, with authors independently selecting the JEL codes for their papers. This introduces subjectivity and potential misclassification, either due to a lack of incentives for careful coding or to strategic behavior aimed at maximizing visibility and citations[12]. Similarly, while each document is assigned to multiple latent topics to maximize the statistical fit of the model, the number of JEL codes assigned to each paper is also left to the discretion of the authors. This means that, beyond the subjectivity in selecting JEL codes, there is also inconsistency in how broadly or narrowly a paper is classified.[13]

Moreover, the Structural Topic Model provides a distribution of topic weights for each paper, while the JEL classification system does not establish a clear hierarchy among the assigned codes, making it difficult to determine their relative importance within a given article. When a paper is classified under multiple JEL codes, there is no indication of which one best represents its core contribution. This poses a challenge for empirical analysis, as researchers must typically assume equal weights across all assigned codes. In practice, this leads to a symmetry assumption—for example, a paper with three JEL codes is assumed to

[12]Kosnik (2017) provides empirical evidence of this issue by analyzing the discrepancy between author-assigned and editor-assigned JEL codes in the American Economic Review (AER) between 1990 and 2008. In this dataset, the AER editorial team reassigned JEL codes to published papers, altering 43% of them, revealing substantial inconsistencies. These changes suggest that authors often misclassify their research, either inadvertently or as a strategic response to perceived trends in citation behavior. The study also finds that some JEL categories, such as C (Mathematical and Quantitative Methods) and D (Microeconomics), tend to be overused by authors, while others are underrepresented, potentially distorting the perceived composition of economic research. These findings underscore a major shortcoming of the JEL system: while it provides a structured taxonomy, its reliance on self-assignment introduces biases that may weaken its reliability as a tool for tracking and analyzing research trends.

[13]In this sense, Kosnik (2017) compares author-assigned and editor-assigned JEL codes in the American Economic Review (AER). The study finds that authors assigned, on average, more JEL codes to their papers than the editors ultimately retained, suggesting a tendency among researchers to overclassify their work. This discrepancy indicates that the incentives guiding authors' choices may differ from the editorial standards applied in formal classification. The overuse of JEL codes by authors can dilute the precision of the system, making it harder to track research specialization and trends accurately.

devote one-third of its focus to each—an assumption that may not hold if some codes reflect central contributions while others are secondary. That said, the JEL system remains a widely used and standardized classification scheme, well understood by editors and researchers alike. Its structure enables consistent tracking of research trends over time and facilitates comparability across studies.

The text analysis approach offers a valuable alternative for addressing research questions traditionally explored using JEL codes. In this paper, our main contribution is to analyze gender citation gaps using latent research topics derived from text analysis, and to compare their performance with that of JEL-based classifications. We show that, in this application, the latent topic approach yields results that are closely aligned with those obtained using JEL codes, supporting its validity as a complementary tool for studying horizontal gender differences in academic publishing.

4 Citation Gender Gaps

In this section, we examine whether female-authored papers receive systematically different citation counts in Top 5 economics journals after accounting for differences in research topics. Building on the methodology introduced in earlier sections, we estimate citation regressions that control for the publication year, the journal, the number of authors and either the JEL classification or the latent research topics identified through the Structural Topic Model (STM). This setup allows us to assess whether the observed citation gap by gender reflects differences in thematic specialization or whether it persists after conditioning on field composition.

We first explain our empirical strategy. To formally assess whether female economists experience systematic differences in citation rates, we rely on a standard linear regression framework commonly used in the literature (see for example Koffi (2021)). In line with previous studies, our empirical model relates the number of citations received by a paper to the gender composition of its authors, controlling for key confounding factors. Specifically, we estimate the following specification:

$$C_{p,t} = \beta_0 + \beta_F F_p + \beta_3 X_p + \gamma_{jt} + \lambda_f + \epsilon_{p,p',t}, \tag{1}$$

where $C_{p,t}$ is the cumulative citations received by paper p.[14] Following standard practice, we apply the inverse hyperbolic sine transformation, $\text{asinh}(C_{pt})$, to the citation variable to ensure that the estimated coefficients can be interpreted as semi-elasticities, even when $C_{pt} = 0$. F_p denotes the proportion of female co-authors on paper p, while X_p captures the total number of authors. λ_f represents fixed effects for research fields, operationalized either through latent topics or JEL codes. The error term ε_{pt} captures unobserved heterogeneity. We estimate the model under two different specifications: one including calendar-year fixed effects (γ_t) to absorb common temporal trends in citation practices, and another including journal-by-year fixed effects (γ_{jt}) to account for time-varying shocks specific to each outlet. The latter specification enables more precise comparisons by restricting variation to articles published in the same journal and year, and—when combined with topic or JEL fixed effects—within the same research field. This approach helps isolate the role of author gender from confounding differences across journals, time periods, or subject areas.

Under specification, the coefficient β_F gives us a clean estimate of the gender citation gap: if it's positive, it suggests that papers with more female authors tend to receive more citations; if it's negative, it suggests a penalty. To ensure our statistical inference is reliable, we cluster standard errors by year (or by journal-year) to allow for the possibility that papers published around the same time might be exposed to similar citation patterns or shocks. Our empirical approach is closely related to that of Koffi (2021), who also examines the relationship between citation outcomes and the gender composition of author teams, controlling for research fields using JEL classification codes. We extend this framework by incorporating not only JEL codes but also latent research topics estimated via structural topic modeling. As discussed in earlier sections, the latent topics show strong alignment with JEL codes while also uncovering additional dimensions of research focus that conventional classifications may overlook—an advantage that proves especially valuable for analyzing citation dynamics.

Table 4 presents our main results. In line with previous studies such as Koffi (2021), Card et al. (2020), and Hengel and Moon (2023), we find that papers written by women

[14] The year subscript t is retained for consistency with the fixed-effects structure, yet each article appears only once—at its publication year—so $C_{p,t}$ represents the cumulative stock of citations tallied at the end of the sample.

tend to receive more citations. Specifically, we estimate a citation advantage of about 16.3 log points when controlling for year, and about 12.1 log points when controlling for both year and journal. This suggests that, on average, female-authored papers are cited more often than comparable male-authored ones, even after adjusting for outlet and time effects.

Table 4 : Regression Results (Letter + 2 digits)

	Total Citations (asinh)					
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion of Female Authors	0.163**	0.121***	0.011	0.025	-0.001	0.025
	(0.045)	(0.045)	(0.045)	(0.046)	(0.053)	(0.006)
Total Number of Authors	0.219***	0.196***	0.178***	0.173***	0.158***	0.142***
	(0.015)	(0.015)	(0.012)	(0.012)	(0.019)	(0.016)
Topic Controls	No	No	Yes	Yes	No	No
JEL Code Controls	No	No	No	No	Yes	Yes
Observations	7,244	7,244	7,244	7,244	4,760	4,760
R^2	0.358	0.412	0.481	0.509	0.530	0.564
Adj. R^2	0.356	0.402	0.475	0.497	0.449	0.475
R^2 Within	0.036	0.030	0.220	0.191	0.303	0.298
Adj. R^2 Within	0.036	0.030	0.214	0.185	0.187	0.181
Std. Errors	Year	Year + Journal	Year	Year + Journal	Year	Year + Journal
FE: Year	Yes		Yes		Yes	
FE: Year + Journal		Yes		Yes		Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered by year in Models (1), (3), and (5), and by journal-year in Models (2), (4), and (6). The inverse-hyperbolic-sine transform is $\text{asinh}(x) = \ln\left(x + \sqrt{x^2 + 1}\right)$, a log-like function that is well-defined at zero.

However, once we control for research fields—either through estimated topics or JEL codes—the gender citation gap largely disappears. The coefficient on the proportion of female authors is positive and statistically significant when the model includes only year fixed effects (Model 1), or both year and journal fixed effects (Model 2). Yet, when we further account for field differences—by including 49 latent topic dummies (Models 3–4) or detailed JEL code fixed effects (Models 5–6)—the estimated gender effect becomes statistically insignificant.[15] In our most comprehensive specification, increasing the share of female co-authors by one standard deviation is associated with a change in expected citations of less than 0.025 log points—a negligible magnitude well within the margin of statistical uncertainty. These results suggest that the initial citation premium for female-authored papers is largely driven by differences in field specialization between men and women, rather than a direct gender effect.[16]

Goodness-of-fit statistics support this interpretation. The overall R^2—which measures how much of the variation in citation counts our model explains—increases substantially, from 0.36 in the basic specification to 0.56 when we control for both research topics and JEL codes. This suggests that a large share of citation differences across papers is linked to the specific field of research. Even more telling is the change in the within-group R^2, which rises from almost zero to 0.29. This means that once we account for when and where a paper was published, most of the remaining variation in citations is still driven by the topic or field the paper belongs to. In other words, the field of research matters—a lot. These results confirm the importance of using the richest possible set of controls when estimating the gender citation gap. Simpler models that ignore field differences tend to overstate the role of gender because they inadvertently capture persistent differences in the kinds of topics men and women work on.

An additional and novel feature of our analysis is the inclusion of team size as a control

[15] In Appendix Tables 10 and 12, we report the estimated coefficients for the field fixed effects—both STM-estimated topics and JEL codes—included in the citation regressions. To maintain clarity and focus, we display only those coefficients that are statistically significant at the 5% level ($p < 0.05$) in Table 10 and statistically significant at the 1% level ($p < 0.01$) in Table 12 . These results provide additional insight into field-specific citation patterns and complement the main analysis presented in the paper.

[16] For completeness, Appendix C replicates the analysis using JEL codes aggregated at two alternative levels: (i) the letter plus one-digit level (Table 9) and (ii) the letter-only level (Table 11). The findings remain broadly consistent, reinforcing the robustness of our conclusions across different specifications of field controls. Table 9 shows the JEL code significant coefficients at the 1% level in Table 11, Model 6.

variable. While previous studies have focused on author gender and field of research, few have systematically accounted for the number of co-authors when analyzing citation dynamics. Across all specifications, we find a strong and robust association between team size and citation outcomes: the estimated elasticity ranges between 0.14 and 0.22. In practical terms, adding one co-author increases expected citations by approximately 15–20 percent, holding other factors constant. This effect remains stable across all models, suggesting that collaboration enhances scholarly visibility or impact independently of research field or journal. One plausible interpretation is that larger teams benefit from greater specialization, broader dissemination networks, or complementary skills.

For robustness, we also consider an alternative gender categorization. Instead of using the proportion of female authors in each coauthor team, we classify author gender composition into three groups: papers with no female authors, papers with a minority share of female authors (0–50%), and papers with a majority of female authors (above 50%). Using this more flexible classification, we replicate our main regression with these categorical indicators. The results remain highly consistent with those obtained using a continuous measure of female author share, providing additional robustness to our findings. We report this alternative specification in Table 5.

[16] For large values of the dependent variable, the inverse hyperbolic sine transformation $\text{asinh}(x)$ approximates $\ln(2x)$. Therefore, the estimated coefficients can be interpreted as approximate semi-elasticities, especially for papers with moderate to high citation counts.

Table 5 : Regression Results (Letter + 2 digits) and 3 Female Groups

	Total Citations (asinh)					
	(1)	(2)	(3)	(4)	(5)	(6)
Between 0% and 50% of female authors	0.070**	0.059*	0.0343	0.041	0.009	0.16
	(0.034)	(0.033)	(0.025)	(0.031)	(0.038)	(0.038)
Above 50% authors	0.155***	0.011**	-0.013	0.001	0.017	0.049
	(0.038)	(0.045)	(0.038)	(0.047)	(0.058)	(0.065)
Total Number of Authors	0.214***	0.191***	0.173***	0.167***	0.157***	0.142***
	(0.013)	(0.014)	(0.011)	(0.013)	(0.020)	(0.017)
Topic Controls	No	No	Yes	Yes	No	No
JEL Code Controls	No	No	No	No	Yes	Yes
Observations	7,244	7,244	7,244	7,244	4,760	4,760
R^2	0.358	0.412	0.481	0.510	0.530	0.564
Adj. R^2	0.356	0.402	0.475	0.497	0.449	0.475
R^2 Within	0.036	0.030	0.220	0.191	0.303	0.298
Adj. R^2 Within	0.036	0.030	0.214	0.185	0.187	0.181
Std. Errors	Year	Year + Journal	Year	Year + Journal	Year	Year + Journal
FE: Year	Yes		Yes		Yes	
FE: Year + Journal		Yes		Yes		Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.Standard errors are clustered by year in Models (1), (3), and (5), and by journal-year in Models (2), (4), and (6). The inverse-hyperbolic-sine transform is $\text{asinh}(x) = \ln\big(x + \sqrt{x^2+1}\big)$, a log-like function that is well-defined at zero.

Our analysis shows that both latent research topics and JEL-based classifications are useful methodologies for analyzing gender citation gaps, as they yield similar results. However, it is also relevant to ask whether one of these approaches offers superior explanatory power when modeling citation outcomes. This question cannot be addressed directly using Table 4, since the sample of papers with JEL codes is smaller. To ensure a fair comparison, we address this question by holding the sample constant.

Specifically, we compare model fit using either JEL codes or STM topics as field controls, restricting the dataset to the subset of papers for which JEL codes are available (as in regressions (5) and (6)). We then re-estimate regression (4) from Table 4 on this same subsample and compute three standard model fit statistics: the adjusted R^2, the Bayesian Information Criterion (BIC), and the Akaike Information Criterion (AIC). The results are presented in Table 6.

Table 6 : Model Fit Comparison Using Different Sets of Controls

Control Variables	**Adjusted R^2**	**Bayesian Information Criterion**	**Akaike Information Criterion**
Topic Codes	0.486	14,280	13,142
JEL Codes	0.475	19,013	13,806

While the adjusted R^2 captures the proportion of variance explained, the AIC and BIC incorporate penalties for model complexity, with lower values indicating a better model. These criteria allow us to evaluate whether any improvement in fit justifies the additional parameters. In our case, the model using topic controls outperforms the one based on JEL codes, with substantially lower AIC and BIC values. This suggests that the STM-based specification offers a better overall balance between explanatory power and parsimony.

5 Conclusions

This paper provides new evidence on gender disparities in citation patterns within the Top 5 economics journals by combining two complementary approaches to classify research content: a data-driven method based on STM-estimated topics, and a standardized taxonomy based on JEL codes. Our main contribution is to show that female-authored papers exhibit a citation premium on average, but that this premium largely disappears once we control for field specialization using either classification. The consistency of results across both systems reinforces the conclusion that horizontal gender differences in research focus—rather than differential treatment in citation behavior—explain most of the observed citation gap.

We do not find direct evidence of gender-based citation bias. However, our results highlight persistent horizontal gender differences in field specialization, and there are plausible mechanisms through which these differences may lead to indirect structural barriers in academic careers. Theoretical models of statistical discrimination in evaluation processes show that if women are underrepresented in editorial boards or evaluation committees, differences in research focus across genders could negatively affect promotion, tenure, and long-term academic recognition. Conde-Ruiz et al. (2022b) introduce the concept of *homo-accuracy bias*, whereby evaluators assess candidates more accurately when they share similar research interests. Similarly, Siniscalchi and Veronesi (2020) describe a form of *self-image bias*, in which evaluators tend to favor candidates who resemble their younger selves. Both models suggest that thematic underrepresentation may reinforce academic inequality, even in the absence of explicit bias.

Data Availability

This study is based on publicly available data, except for the citation data, which was provided by RePEc (Research Papers in Economics). Access to these citation data is subject to RePEc's terms of use and data-sharing policies.

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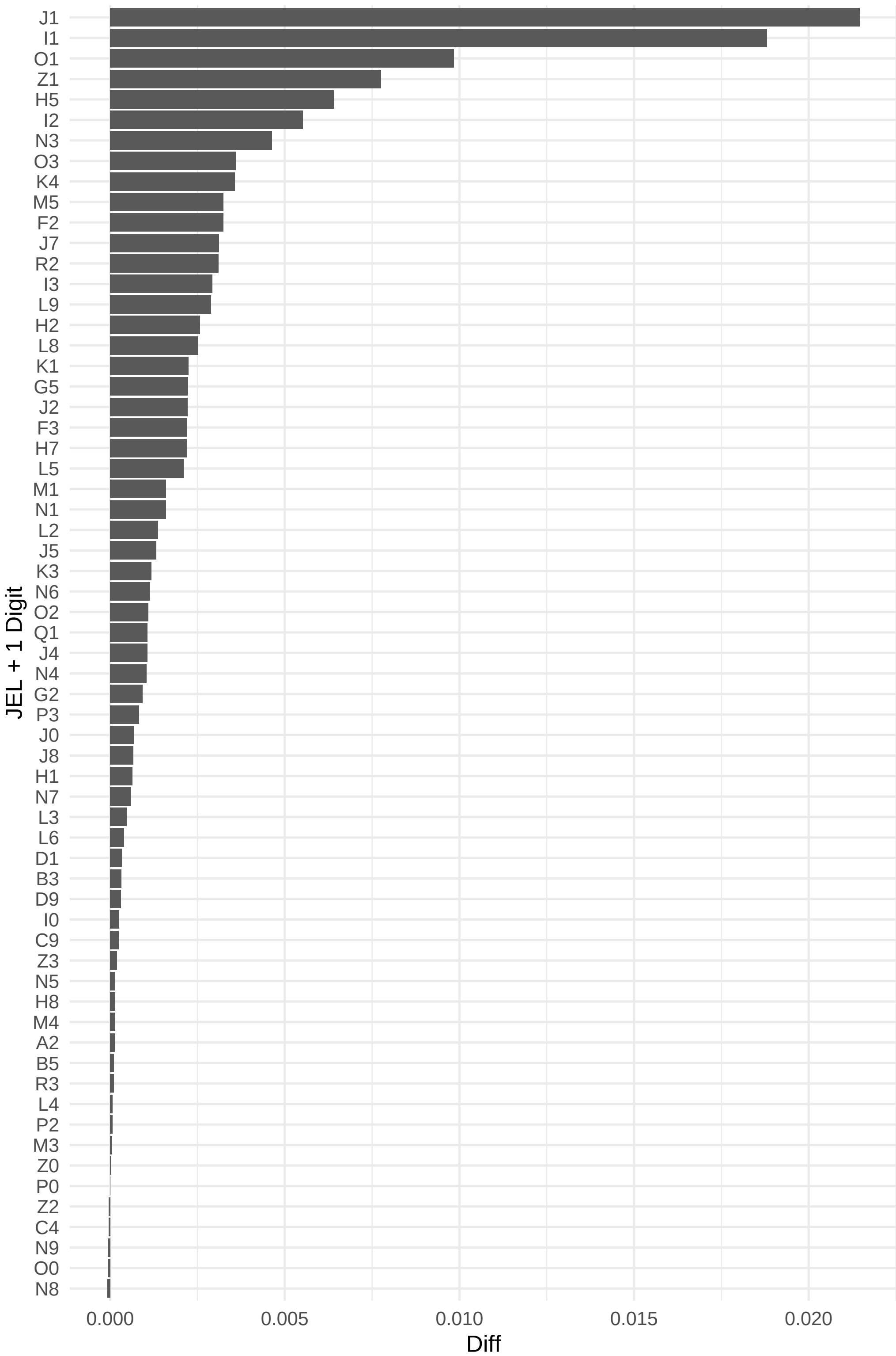
A Conditional Empirical Distribution across Topics between Male and Female.

Table 7 : Conditional Distribution of Topics by Gender

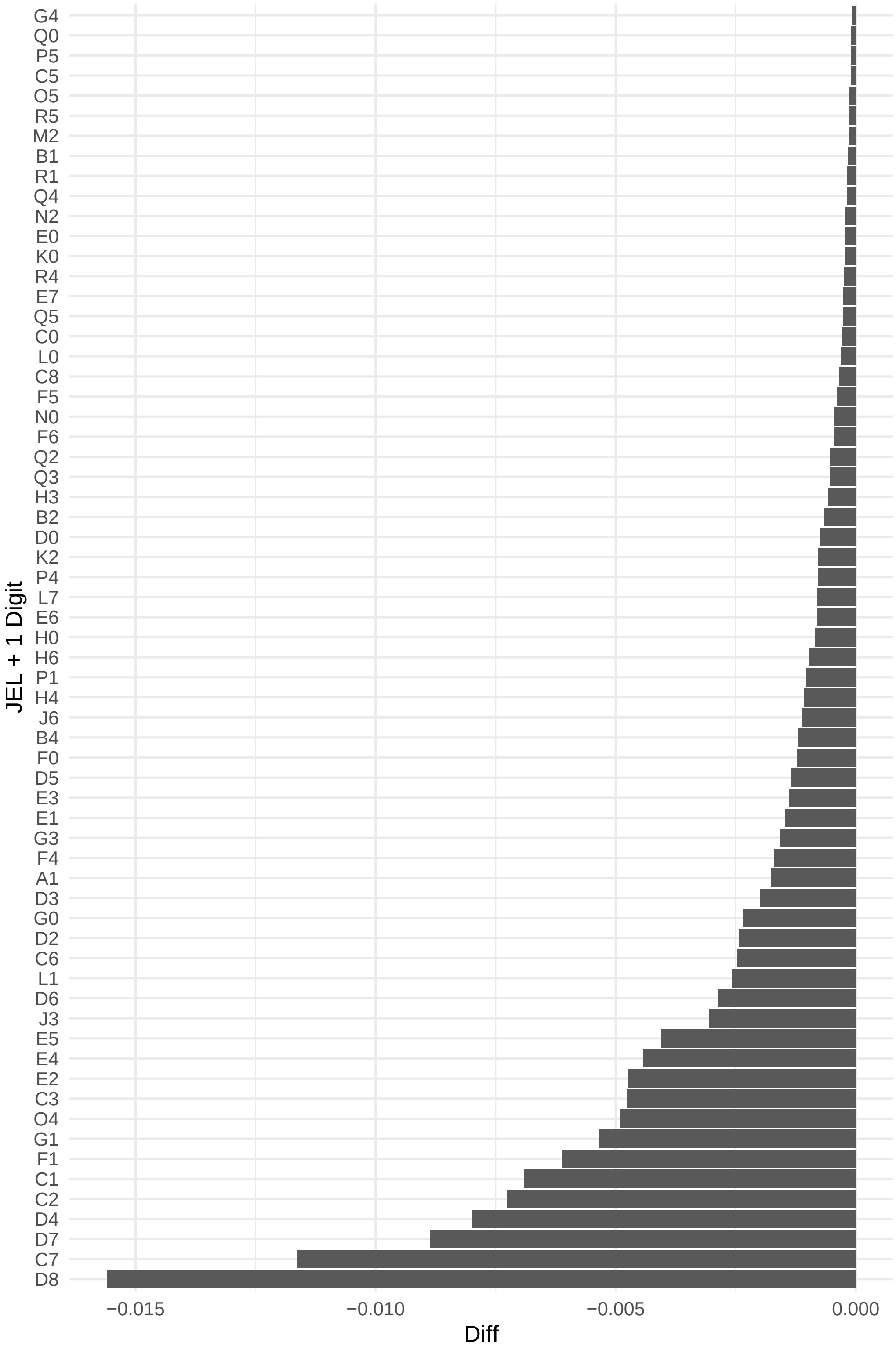
Topics 1–25			Topics 26–50		
Topic	**Female**	**Male**	**Topic**	**Female**	**Male**
Topic 1	0.0151	0.0189	**Topic 26**	0.0085	0.0101
Topic 2	0.0096	0.0117	**Topic 27**	0.0151	0.0185
Topic 3	0.0201	0.0236	**Topic 28**	0.0087	0.0088
Topic 4	0.0261	0.0213	**Topic 29**	0.0202	0.0209
Topic 5	0.0193	0.0252	**Topic 30**	0.0152	0.0132
Topic 6	0.0135	0.0150	**Topic 31**	0.0191	0.0213
Topic 7	0.0091	0.0105	**Topic 32**	0.0284	0.0268
Topic 8	0.0183	0.0327	**Topic 33**	0.0167	0.0136
Topic 9	0.0132	0.0158	**Topic 34**	0.0308	0.0309
Topic 10	0.0162	0.0235	**Topic 35**	0.0231	0.0248
Topic 11	0.0252	0.0203	**Topic 36**	0.0098	0.0141
Topic 12	0.0262	0.0285	**Topic 37**	0.0079	0.0083
Topic 13	0.0472	0.0508	**Topic 38**	0.0207	0.0243
Topic 14	0.0210	0.0182	**Topic 39**	0.0148	0.0179
Topic 15	0.0241	0.0276	**Topic 40**	0.0167	0.0120
Topic 16	0.0414	0.0195	**Topic 41**	0.0303	0.0254
Topic 17	0.0158	0.0138	**Topic 42**	0.0296	0.0349
Topic 18	0.0226	0.0195	**Topic 43**	0.0262	0.0160
Topic 19	0.0158	0.0163	**Topic 44**	0.0171	0.0140
Topic 20	0.0281	0.0193	**Topic 45**	0.0190	0.0201
Topic 21	0.0292	0.0279	**Topic 46**	0.0125	0.0118
Topic 22	0.0310	0.0280	**Topic 47**	0.0245	0.0373
Topic 23	0.0266	0.0123	**Topic 48**	0.0233	0.0237
Topic 24	0.0095	0.0111	**Topic 49**	0.0150	0.0179
Topic 25	0.0185	0.0183	**Topic 50**	0.0042	0.0040

Figure A. 1 : Difference of the Empirical distributions across Primary JEL codes + 1 Digit between males and females (conditional on having published an article in Top 5). Part I.



Note:

Figure A. 2 : Difference of the Empirical distributions across Primary JEL codes + 1 Digit between males and females (conditional on having published an article in Top 5). Part II.



Note:

B Linking Latent Estimated Research Topics to JEL codes

In this appendix, we aim to disentangle the existing relationship between the topics uncovered by a structural topic model (STM) and the JEL codes assigned to articles in our sample. Suppose we have a set of n documents. The STM estimation yields a topic-distribution vector for each document,

$$\theta_d = \big(\theta_{d,1},\, \theta_{d,2}, \dots,\, \theta_{d,k}\big), \quad \sum_{t=1}^{k} \theta_{d,t} = 1,$$

where k is the total number of extracted topics, and $\theta_{d,t}$ indicates the proportion of document d's content assigned to topic t. We can rewrite the topic-distribution vector as a matrix $\theta_d \in M_{k\times 1}$. Similarly, each document d is allocated to a set of JEL codes.

$$\gamma_d = \big(\gamma_{d,1},\, \gamma_{d,2}, \dots,\, \gamma_{d,\mathcal{J}}\big)$$

Where $\mathcal{J}$ is the number of JEL codes under consideration (i.e. primary, secondary or tertiary JEL classification) and $\gamma_{d,j}$ is equal to 1 if the JEL code j has been assigned to document d and it is 0 otherwise. We can rewrite this document-JEL codes vector as a matrix $\gamma_d \in M_{1\times\mathcal{J}}$.

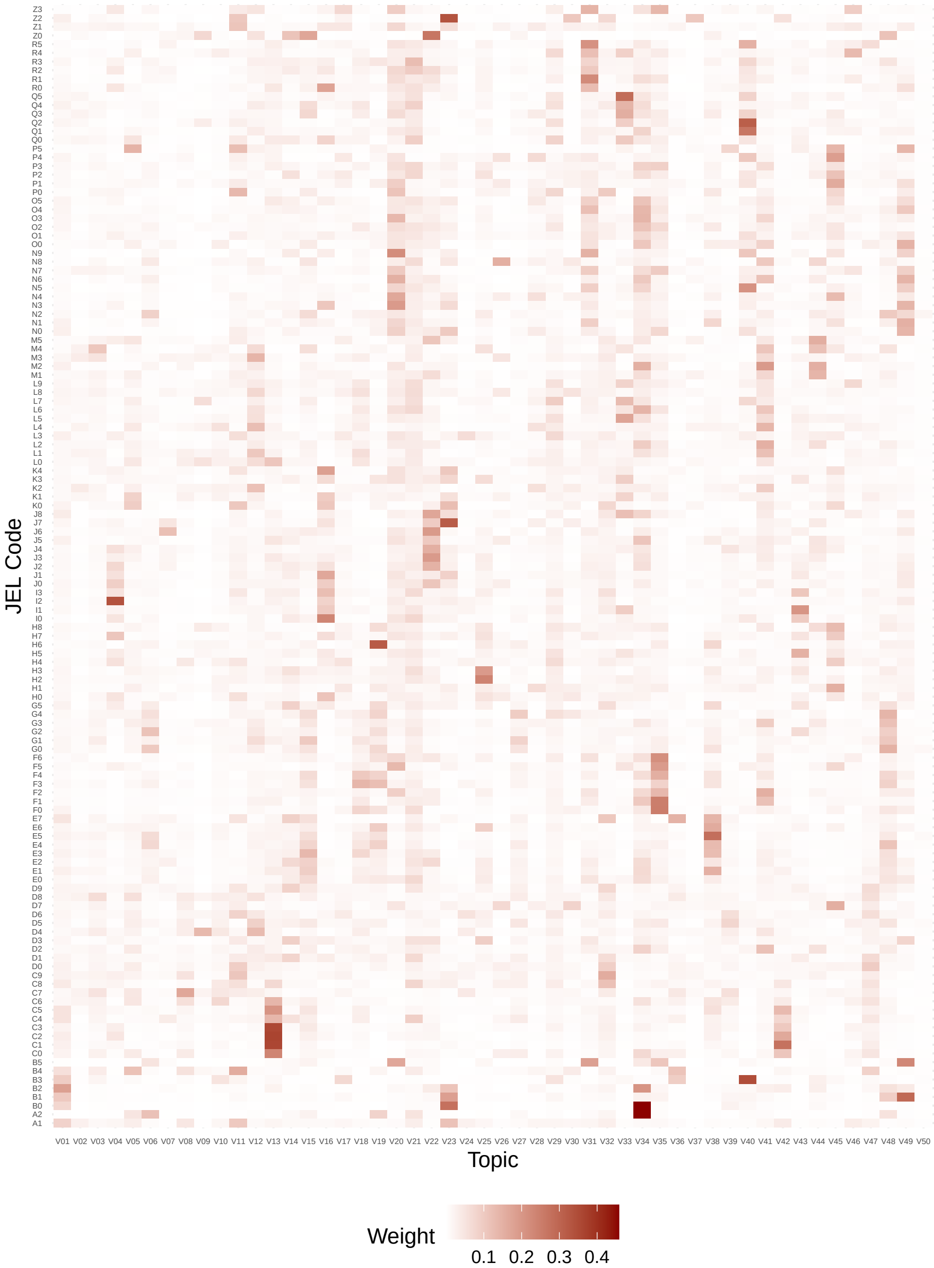
To connect topics to the JEL codes, for each document d, we multiply the topic-distribution matrix $\theta_d \in M_{k\times 1}$ by JEL codes matrix $\gamma_d \in M_{1\times\mathcal{J}}$ this generates a matrix $k \times |\mathcal{J}|$ matrix M^d, where $M^d_{t,j}$ is for document d the topic-t weight if the JEL code j has been also assigned to d (and 0 otherwise). We define an aggregate matrix M by summing over all documents, the matrices M^d.

We normalize M to $\widetilde{M}$ by homogenizing the total weight of the columns to 1, in order to facilitate interpretation. Under this column normalization, each column j becomes a probability distribution over topics:

$$\widetilde{M}_{t,j} = \frac{M_{t,j}}{\sum_{t=1}^{k} M_{t,j}},$$

so that $\widetilde{M}_{t,j}$ represents the topic t weight for JEL code j. In effect, this transformation

Figure A. 3 : Correspondences between JEL Codes (1-Digit) and Topics.



reveals how each JEL code is composed of the various STM-derived topics. Figure 14 in the main text and Figure 3 in the appendix, display the normalized correspondence matrix $\widetilde{M}$ between STM-derived topics (rows) and JEL codes (columns) as heatmaps.

C Additional regressions

Table 8 : Regression Results (Just letter)

	(1)	(2)	(3)	(4)	(5)	(6)
`p_fem`	0.162**	0.120**	0.011	0.025	0.017	0.029
	(0.045)	(0.044)	(0.042)	(0.046)	(0.052)	(0.055)
`n_aut`	0.219***	0.196***	0.178***	0.173***	0.186***	0.168***
	(0.014)	(0.014)	(0.012)	(0.012)	(0.017)	(0.015)
Topic Controls	No	No	Yes	Yes	No	No
JEL Code Controls	No	No	No	No	Yes	Yes
Observations	7,226	7,226	7,226	7,226	4,760	4,760
R^2	0.358	0.412	0.481	0.510	0.403	0.441
Adj. R^2	0.356	0.402	0.475	0.497	0.397	0.423
R^2 Within	0.036	0.030	0.220	0.191	0.114	0.100
Adj. R^2 Within	0.036	0.030	0.214	0.185	0.110	0.096
Std. Errors	Year	Year + Journal	Year	Year + Journal	Year	Year + Journal
FE: Year	Yes		Yes		Yes	
FE: Year + Journal		Yes		Yes		Yes

Notes: $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Models (5)–(6) include JEL code fixed effects (not reported).

Table 9 : Regression Results (Letter + 1 digit)

	(1)	(2)	(3)	(4)	(5)	(6)
`p_fem`	0.154**	0.107*	0.011	0.025	0.031	0.064
	(0.047)	(0.046)	(0.042)	(0.046)	(0.058)	(0.054)
`n_aut`			0.178***	0.173***	0.179***	0.162***
			(0.012)	(0.012)	(0.018)	(0.015)
Topic Controls	No	No	Yes	Yes	No	No
JEL Code Controls	No	No	No	No	Yes	Yes
Observations	7,226	7,226	7,226	7,226	4,760	4,760
R^2	0.335	0.395	0.481	0.510	0.449	0.477
Adj. R^2	0.333	0.384	0.475	0.497	0.431	0.448
R^2 Within	0.001	0.001	0.220	0.191	0.183	0.170
Adj. R^2 Within	0.001	0.001	0.214	0.185	0.160	0.146
Std. Errors	Year	Year + Journal	Year	Year + Journal	Year	Year + Journal
FE: Year	Yes		Yes		Yes	
FE: Year + Journal		Yes		Yes		Yes

Notes: $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Models (5)–(6) include JEL code fixed effects (not reported).

Table 10 : Topic significant coefficients at the 5% level in Model 4, Table 4.

Variable	Coefficient	Std. Error	p-Value	Keywords
T11	2.239**	1.136	0.049	behavior, individu, peopl, self
T20	2.259**	1.131	0.046	effect, immigr, innov, increas
T31	2.504**	1.131	0.027	growth, citi, distribut, popul
T34	2.483**	1.112	0.026	product, technolog, sector, industri
T38	2.451**	1.106	0.027	polici, monetari, rate, inflat
T41	2.378**	1.146	0.038	firm, product, profit, entri

Note: $^{**}p < 0.05$. Model 4 includes Journal and Year as combined fixed effects, and also includes Topic as a control. Only topics coefficients statistically significant at 5% are reported in the table.

Table 11 : JEL code significant coefficients at the 1% level in Model 6, Table 8.

Variable	**Coef.**	Description
jel_C	-0.118***	Microeconomics.
jel_E	0.427***	Macroeconomics and Monetary Economics.
jel_F	0.441***	International Economics.
jel_J	0.247***	Labour and Demographic Economics.
jel_O	0.320***	Economic Development, Innovation, Technological Change, and Growth.
jel_Q	0.237***	Agricultural and Natural Resource Economics; Environmental and Ecological Economics.
jel_R	0.341***	Urban, Rural, Regional, Real Estate, and Transportation Economics.

Table 12 : JEL code significant coefficients at the 1% level in Model 6, Table 4

Variable	**Coef.**	**Variable**	**Coef.**	**Variable**	**Coef.**	**Variable**	**Coef.**	**Variable**	**Coef.**
jel_B19	-1.302***	jel_B22	-0.913***	jel_B29	-1.302***	jel_B52	0.783***	jel_C20	-2.521***
jel_C34	-0.930***	jel_C49	0.416***	jel_C61	-0.485***	jel_C68	-1.982***	jel_C69	-1.993***
jel_C73	-0.571***	jel_C80	1.554***	jel_D00	0.750***	jel_D03	0.383***	jel_D29	0.428***
jel_D44	-0.314***	jel_D46	1.072***	jel_D53	-0.538***	jel_D69	0.584***	jel_D71	-0.562***
jel_D79	0.428***	jel_D80	-0.516***	jel_D82	-0.362***	jel_D83	-0.207***	jel_D86	-0.387***
jel_E11	1.616***	jel_E20	0.506***	jel_E22	0.440***	jel_E29	-1.482***	jel_E41	-0.779***
jel_E44	0.288***	jel_E61	-0.592***	jel_E62	0.295***	jel_E70	0.950***	jel_F00	-0.856***
jel_F12	0.622***	jel_F17	0.989***	jel_F19	-1.676***	jel_F20	0.894***	jel_F24	0.598***
jel_F31	0.375***	jel_F37	-1.081***	jel_F38	-1.064***	jel_G13	-0.711***	jel_G18	0.529***
jel_G20	0.617***	jel_G40	-0.775***	jel_G50	-0.522***	jel_H10	0.596***	jel_H12	-0.919***
jel_H89	-0.929***	jel_I12	0.262***	jel_J19	0.937***	jel_J29	1.828***	jel_J50	0.721***
jel_J70	1.161***	jel_J80	1.782***	jel_J82	-1.512***	jel_K23	1.437***	jel_K32	0.965***
jel_K36	0.695***	jel_L39	-1.480***	jel_L51	-0.565***	jel_L53	0.958***	jel_L80	-1.296***
jel_L89	-1.323***	jel_M10	1.485***	jel_M16	1.728***	jel_M21	-0.657***	jel_M38	0.591***
jel_M51	-0.494***	jel_M55	1.089***	jel_N00	1.482***	jel_N01	2.426***	jel_N47	0.716***
jel_N55	1.827***	jel_N64	-1.557***	jel_N82	2.449***	jel_N94	0.752***	jel_O21	-0.885***
jel_O51	1.307***	jel_Q24	-1.176***	jel_Q30	-1.733***	jel_Q41	0.782***	jel_Q43	1.861***
jel_Q47	-0.793***	jel_Q55	-1.893***	jel_R15	-1.998***	jel_R21	0.395***	jel_R28	-3.007***
jel_R33	1.903***	jel_Z21	1.076***	jel_A10	1.043***	jel_A20	2.035***		

Note: $^{***}p < 0.01$. Model 6 includes Journal and Year as combined fixed effects, and also includes JEL codes as a control. Only statistically significant at 1% level coefficients are reported in the table.