Application for Digital Economics and AI Tutorial

Luisa Wall

CONTACT INFORMATION

Name	Luisa Wall
Email	walllu@bc.edu
Affiliation	PhD Candidate at the Department of Economics, Boston College
Address	Maloney Hall, 140 Commonwealth Avenue, Chestnut Hill, MA 02467
Phone	+1 8575404800
BC Web Page	Luisa Wall

GRADUATE STUDY

PhD in Economics, Boston College, enrolled in the academic year 2024/2025

I am a third-year PhD Student, having recently completed my coursework. During the first year, I attended the core classes in math, statistics, econometrics, macro and micro theory. I completed my first-year comprehensive exams in macro and micro at the beginning of June 2025. In the summer of the first year, I worked as a research assistant for Susanto Basu. I continued my RA work with him during the second year, and in summer 2026. The main outcome of this RA work is the co-authored project "Macroeconomic implications of rising markups".

In my second year, I completed the macro and international finance course sequences. Among the classes that most sparked my interest in research on innovation, is the course on producer and worker heterogeneity, taught by Lukas Freund. Following Lukas's suggestion, I did an exercise using the USPTO patent data: constructing a dataset linking **AI patents** to cited technologies, I explored which technologies AI inventions build on and how these have changed over time, from 1980 to 2023.
I also had the opportunity to discuss a proposal about **AI diffusion and productivity growth**, reviewing the literature on General Purpose Technologies (Bresnahan and Trajtenberg, 1995), and the models of technology adoption and diffusion with heterogeneous firms (Benhabib et al., 2021; Perla and Tonetti, 2014). I read the work on AI by Agrawal et al. (2018). For the proposal, I learned about data sources on adoption and diffusion of AI and other technologies. In this class, I gained some computational skills, solving and coding the Hopenhayn (1992) and Hopenhayn and Rogerson (1993) models, and the Shimer and Smith (2000) heterogeneous agents search model.

The other macro classes I attended at Boston College are computational methods in macro with Pablo Guerron, and a class on HANK models, search and matching models, and information, with Robert Ulbricht. Outside my fields, I attended a game theory class. At MIT, I took a class on risk-centric macroeconomics with Ricardo Caballero, and on identification in macro with Chris Wolf.

RESEARCH INTERESTS AND PROJECTS

Research Interests

My fascination with technology and how it shapes labor markets and productivity began long ago: my undergraduate thesis was "The impact of ICT on wage inequality in OECD countries". The recent developments in AI, and the debate around its economic impact, have really strengthened my interest. I am interested in topics related to the **macroeconomic impact of AI and other technologies**: firm adoption and diffusion, effects on the labor market, productivity, and growth. Recently, I have focused on **task-based models**, and using **micro data** to answer these questions. I am interested in **micro approaches to measure technology adoption** and its effects. The Tutorial is an opportunity to learn more about the frontier in **digital economics**. I haven't worked on it yet, but the framing as a fall in specific economic costs and platforms as matching markets (Goldfarb and Tucker, 2019) connects well to my background.

Working papers

- **Weak links and the labor market effect of automation** I provide an extended abstract in **the section below**. *Advisors*: Susanto Basu, Lukas Freund.
- **Macroeconomic implications of rising markups, *joint with Susanto Basu*** This paper asks whether the strong rise in the aggregate markup since 1980, computed as in De Loecker et al. (2020), has counterfactual implications for the US macroeconomy. We feed the markup shocks from the De Loecker et al. (2020) series into the business cycle model with two investment shocks from Justiniano et al. (2011). Looking at the heterogeneity behind the aggregate rising markup series, we notice that the upward trend is driven by a smaller set of firms with low direct production costs, and high overhead costs- concentrated in tech, finance, and services. This dynamic is related to the increasing importance of investments in **intangibles**, and to the growth of the **digital economy**.
- **Are US bonds still a safe haven?** (*This paper is in international finance and not related to the topics of the Tutorial*.) Using Treasury holdings and flow data by investor sector, I document that since the GFC the foreign official share of Treasuries has fallen and been absorbed mainly by domestic and foreign private investors: there is no generalized foreign flight from Treasuries, but the marginal buyer has shifted toward market-based investors. This shift coincides with a declining Treasury convenience yield (Du et al., 2025). I rationalize the empirical findings in a preferred-habitat portfolio model in the spirit of Vayanos and Vila (2021), where an official withdrawal or a supply increase must be absorbed by risk-averse private investors, at a higher risk premium. My next step is to distinguish a higher required return on Treasuries from an actual loss of safe-haven status, providing evidence on the competing assets divesting investors are moving into. *Advisors*: Rosen Valchev, Jaromir Nosal.

Weak links and the labor market effect of automation *(extended abstract)*

In 1967, Baumol illustrates an empirical puzzle: uneven productivity growth across sectors results in higher wages and a larger production cost share spent on the sectors that grow slower. Complementarity across sectors lies at the heart of this dynamic. In this paper, I engage with the idea that **complementarities** across tasks matter for how capital-embodied technological progress, in the form of automation, shapes labor market outcomes. Task-based models of automation are the canonical framework for studying automation. Many of the conclusions on the growth and productivity impact of automation hinge on the **elasticity of substitution**

across tasks[1]. Whether tasks are substitutes or complements affects the sign of how capital-improving progress at already automated tasks affects the labor share. Automation- a labor displacing form of technological change- reduces the aggregate labor share regardless of σ. Still, only when tasks are complements, automation raises the relative shadow value of tasks left to labor. These tasks act as *bottlenecks* or *weak links* in production, increasing the marginal value, and potentially the wages of workers performing them.

Despite the importance of this parameter, current literature provides thin evidence on the elasticity of substitution across tasks. The first contribution of this paper is to propose a structural approach to measure the elasticity from **worker-level data**. I use the task and wage data in BIBB/BAuA Employment Surveys. I derive a structural wage equation from a simple task-based model with Fréchet task-specific productivities. Workers hold positive time shares over every observed task category, while each micro-task is performed by the worker or unit of capital with the highest productivity in that task, so that **specialization** and **interior observed shares** hold simultaneously. The wage equation is used to recover occupation-specific relative task prices. Then, I estimate σ from the response of relative labor task expenditure shares to relative task prices, controlling for the automation margin. To proxy the occupational-level task automation share, I construct indices using the automation scores from Webb (2019) and the German stocks of AI, robots and software.

My preliminary estimate of the elasticity σ is not statistically distinguishable from the Cobb-Douglas case. The coefficient on automation is significant, and has the expected sign. The labor approach suffers from some limitations. Worker-level data do not contain information about the share of task expenditure on capital. Task prices backed out from wages are estimated regressors, and are volatile due to limited observations available for each combination of time period and occupation in the survey data. I am currently working on improving this estimation.

Given these limitations, my second contribution is to use the simple task-based model of automation in Hassanein and Steinsson (2026), [2] to illustrate three theoretical implications of complementarity that can be tested using **firm-level data**, and do not require to observe task quantities or prices. The key intuition is that the labor share and the relative price of labor rise in response to intensive capital improvement- unlike automation. I am currently working on the empirical implementation of these tests, using firm-level data.

Testing for complementarities across tasks is the first step toward exploring relevant **implications for the labor market**. Automation can shrink the labor share of output and simultaneously raise the wage of the worker performing the bottleneck task. Whether technologies such as AI or robots actually impoverish workers or benefit them may depend less on how many of their tasks these technologies can perform, and more on how needed and irreplaceable the remaining human tasks are. My next steps involve estimating what the actual empirical skill distribution of workers implies for wages, introducing heterogeneity in skills, task content, and ultimately outcomes.

[1] See, for example, Aghion et al. (2017), Jones and Liu (2024), Gans and Goldfarb (2026), Jones and Tonetti (2026).
[2] The authors build on previous work by Zeira (1998), Aghion et al. (2017), Acemoglu and Restrepo (2018).

REFERENCES

Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 4B, pp. 1043–1171. Amsterdam: Elsevier.

Acemoglu, D. and P. Restrepo (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review* 108(6), 1488–1542.

Aghion, P., B. F. Jones, and C. I. Jones (2017). Artificial intelligence and economic growth. NBER Working Paper 23928, National Bureau of Economic Research.

Agrawal, A., J. Gans, and A. Goldfarb (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Boston, MA: Harvard Business Review Press.

Baumol, W. J. (1967). Macroeconomics of unbalanced growth: The anatomy of urban crisis. *American Economic Review* 57(3), 415–426.

Benhabib, J., J. Perla, and C. Tonetti (2021). Reconciling models of diffusion and innovation: A theory of the productivity distribution and technology frontier. *Econometrica* 89(5), 2261–2301.

Bresnahan, T. F. and M. Trajtenberg (1995). General purpose technologies 'engines of growth'? *Journal of Econometrics* 65(1), 83–108.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The rise of market power and the macroeconomic implications. *Quarterly Journal of Economics* 135(2), 561–644.

Du, W., R. Keerati, and J. Schreger (2025). Decoupling dollar and Treasury privilege. NBER Working Paper 35000, National Bureau of Economic Research.

Gans, J. S. and A. Goldfarb (2026). O-ring automation. NBER Working Paper 34639, National Bureau of Economic Research.

Goldfarb, A. and C. Tucker (2019). Digital economics. *Journal of Economic Literature* 57(1), 3–43.

Hassanein, A. and J. Steinsson (2026). A simple introduction to task-based models of technical change.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica* 60(5), 1127–1150.

Hopenhayn, H. and R. Rogerson (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy* 101(5), 915–938.

Jones, B. F. and X. Liu (2024). A framework for economic growth with capital-embodied technical change. *American Economic Review* 114(5), 1448–1487.

Jones, C. I. and C. Tonetti (2026). Past automation and future A.I.: How weak links tame the growth explosion. Working paper.

Justiniano, A., G. E. Primiceri, and A. Tambalotti (2011). Investment shocks and the relative price of investment. *Review of Economic Dynamics* 14(1), 102–121.

Kremer, M. (1993). The O-ring theory of economic development. *Quarterly Journal of Economics* 108(3), 551–575.

Perla, J. and C. Tonetti (2014). Equilibrium imitation and growth. *Journal of Political Economy* 122(1), 52–76.

Shimer, R. and L. Smith (2000). Assortative matching and search. *Econometrica* 68(2), 343–369.

Vayanos, D. and J.-L. Vila (2021). A preferred-habitat model of the term structure of interest rates. *Econometrica* 89(1), 77–112.

Webb, M. (2019). The impact of artificial intelligence on the labor market. Working paper.

Zeira, J. (1998). Workers, machines, and economic growth. *Quarterly Journal of Economics* 113(4), 1091–1117.