Research Output Before and During the Pandemic*

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First Draft: August 2022
This Draft: March 2024

PRELIMINARY
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Abstract

We find a significant and robust increase in research output during the work-from-home protocols put in place due to the COVID-19 pandemic. Collaboration as measured by authors per paper also significantly increased over this time period. In addition, those in the bottom half of the output distribution prior to the pandemic experienced the largest gains, effectively reducing inequality among researchers. Increased output, collaboration, and gains at the bottom of distribution contrast with findings elsewhere in the literature. However, divergences across studies and populations studied can be reconciled within a standard principal-agent model once we acknowledge pre-existing differences in the flexibility of hours and the use of incentive contracts across different occupations. Our results are consistent with high-skilled occupations—which typically feature flexible hours and incentive contracts—effectively receiving an increase in their time endowment. To evaluate the welfare implications, we show that in a general equilbrium endogenous growth model, the increased time endowment is also associated with higher economic growth, lower inflation and lower interest rates.

JEL: A11, E24, J24, J33, M52
Keywords: Remote work, Research Productivity, Principal-Agent, Endogenous Growth

*The views expressed herein are our own and do not necessarily reflect the views of our employer.
We are grateful to Cevat Aksoy, Jose Maria Barrero, Nick Bloom, Prithwiraj Choudhury, Steven Davis, Natalia Emanuel, and Emma Harrington for helpful discussions and for valuable comments. We thank conference and seminar participants at the 2023 Remote Work Conference (Stanford).

1 Introduction

What effects do fully remote work policies have on productivity? As highlighted in Barrero, Bloom and Davis (2023), recent research suggests that fully remote work may reduce productivity compared to more traditional on-site arrangements. This perspective is often supported by studies of call center and data entry workers, where a lack of motivation and discipline among employees has been noted as a key issue.(Emanuel and Harrington, 2021; Atkin, Schoar and Shinde, 2023) However, the generalizability of these findings to the broader knowledge workforce remains unclear. What about workers who tend to be highly skilled with advanced degrees? On this front, Kruger, Maturana and Nickerson (2020) finds that among the top-50 academic departments, productivity increased by 35% during the pandemic. That said, Jiang, Rösch, Liu and Tiu (2022) examine the top 1,000 schools and find an overall decline in productivity. These striking differences in productivity outcomes present a bit of a puzzle, not only across professions but also within them.

We provide novel empirical evidence on research productivity, rationalize this puzzle of divergent outcomes with a theoretical model, and provide a general equilibrium growth model in which we explore welfare implications. We show that the variation in productivity is in fact consistent with the predictions of a standard principal-agent model once we acknowledge pre-existing differences in the use of incentive contracts across different occupations and job-characteristics. With the model's intuition in-hand, we take a new approach to the research productivity question by focusing on authors from the Federal Reserve system when they were fully remote, a group that was explicitly excluded from the previous studies. This group is relatively unique as they did not face the significant costs of increased time spent on teaching and reformulating curriculums during the pandemic. By not being subject to this issue, this group of individuals may provide an alternative perspective on the potential effects of remote work policies on output.

To better understand the potential effect of fully remote policies on output of system economists, we hand-collected the number of working papers produced on a quarterly basis for over 1,000 economists in the Federal Reserve system dating back to 2018. We also tracked a number of author-specific characteristics, such as age, gender, and the time period in which each of the economists worked in the Federal Reserve system. While the production of working papers is just one dimension of output, we view it as a parsimonious and sensible proxy given the difficulty of tracking other important aspects such as policy-related work, and view any potential issues with this proxy as likely to be true both before and during the pandemic.

Our main finding is that research output increased by over 20% across the Federal Reserve system when considering potential authors who were present both before and during the pandemic. This large increase holds regardless of whether we use poisson or linear regressions, and whether or not we include author fixed effects. This magnitude is significantly larger than the productivity gains found in most of the studies listed above and not far from those in Kruger, Maturana and Nickerson (2020), which focused on SSRN postings from top-50 academic departments.

One potential concern is that the increase in output is less about remote work policies and more about the pandemic shock generating new research ideas. Part of this view rests on the assumption

that time was not the limiting factor prior to the pandemic but instead it was a lack of ideas. We try to partially address this concern in a number of ways. First, we exclude the year 2020 from our analysis, as some may wonder if there was merely a surge that quickly reverted. We find the boost in output remains strong and statistically significant. We also exclude papers with the words "covid" and "pandemic" in the title and again, our results continue to hold. Lastly, we compare the time period to the Global Financial Crisis, another situation in which there was a significant new shock to do research on, but had no changes in WFH policies. We find for that particular time period, there was actually a decrease in the amount of research produced across the system, which contrasts with what we observe during the pandemic.

To shed light on who was driving this increase in research output, we first split the sample into an upper and lower half based on output per quarter per author prior to the pandemic. Upon doing so, we find that the upper half in terms of pre-pandemic output continued to have high output, and thus was little changed. In contrast, the bottom half of the distribution exhibited a substantial increase in output. In other words, the inequality in terms of output between the lower and upper half of the distribution was dramatically reduced. This reduction in inequality between the two halves of the distribution is in contrast to the studies that focus on academia. In Jiang, Rösch, Liu and Tiu (2022) and Kruger, Maturana and Nickerson (2020), they found that the top departments were most responsible for any increase in output, which effectively increased inequality across researchers and universities.

We also explore differences across age groups and gender. To proxy for age, we use years since completion of PhD. Similar to previous studies, we split the groups up into those that have completed their PhD in the last 8 years, those between 8 years and 22 years, and those 22 years and after. We find that the youngest cohort experienced the largest gains and the oldest also experienced relative gains. In contrast, the middle group (which had the largest output prior to the pandemic), did not improve as much as the other two cohorts, although their output still significantly increased over this time period. In terms of gender, we find no significant difference over the pandemic, which is in contrast to other studies that found females produced less during the pandemic.

Subsequently, we also examine effects on collaboration as measured by authors per paper. One concern is that WFH policies may have reduced collaboration. Instead, we find a significant increase in collaboration across the system during this time period, and this finding is also robust to the incorporation of a time trend.

Finally, we further distinguish our work from previous studies by taking two theoretical approaches to understanding our findings. The first approach is focused on explaining the heterogeneous outcomes (negative effects for call center workers versus positive effects for economists) with a principal-agent model. The second approach involves a structural general equilibrium model that allows us to study the potential implications this might have on macroeconomic aggregates.

With respect to the first approach, one way to rationalize differential effects of remote work on productivity, without appealing to heterogeneity in the cost of effort, is through a standard

principal-agent framework that allows for heterogeneity in the pre-existing cost of monitoring. Consider two possible occupations. The first occupation, which might represent a call center or data entry worker, entails sufficiently low monitoring costs when a worker is on-site such that the firm can perfectly observe worker effort and implement a profit maximizing first-best contract that induces higher effort from the worker. Shifting this occupation to remote increases the costs of monitoring: at the extreme, the firm can only observe the worker's output. In this more uncertain environment, where the wage is determined by output rather than effort, the risk averse worker may wish to avoid states in which high effort potentially generates low output. If this is the case, a constrained-efficient incentive contract that specifies lower effort becomes optimal, all else equal (i.e. even if the cost of effort is unchanged). Thus, observing a decrease in output does not necessarily imply an increase in effort costs. More generally, this scenario conflates changes in the cost of effort with changes in the incentives to put forth effort provided by the contract. If this scenario is not ruled out, a study may infer a larger increase in the cost of effort due to remote work than actually exists.

For the second occupation, which might reflect a professor or economist, monitoring costs are high regardless of work location. Research papers, for example, entail high monitoring costs because they can take years to write and follow numerous paths to completion. In this setting, the constrained-efficient incentive contract would also be output-based, whether it is in-person or remote. Therefore, unlike the first occupation, there is no shift in the structure of the contract when moving to remote. Without a change in the nature of the contract, effort costs become the dominant mechanism affecting worker output in moving to remote, the largest of which could be those associated with commuting. By reducing these costs, the worker is willing to produce more for a given wage, which translates into greater output.

What about heterogeneity within an occupation such as academics? In this case, the dominant mechanism is likely to be different effort costs associated with remote work. It's plausible that the costs of effort were reduced for those focused on research when they were remote, while those positions with greater focus on teaching faced greater costs due to changes in curriculum.

To consider aggregate implications, we employ a structural New-Keynesian endogenous growth model to simulate an exogenous boost in the time endowment. This increase in the time endowment aligns with the significant decrease in commuting time due to work-from-home (WFH) policies, as reported by Bloom, Han and Liang (2022). They find that the average employee saves around 70 minutes a day, eliminating commute and preparation time for office.

Our theoretical simulations suggest the increased time allotted to households is split between additional labor and leisure. This contrasts with the typical intratemporal preference shock scenario, where labor and leisure are inversely related. The extra labor supply leads to growth in output and consumption, and also bolsters the accumulation of ideas and investment in research and development (R&D). Likewise, the spillovers from the R&D investment contribute to a surge in aggregate productivity growth. The increased productivity and the rise in the labor supply helps reduce marginal costs and inflation, lowering the nominal risk-free rate while increasing the 10-year

minus 3 month spread.

Overall, our findings suggest that the effects of fully remote work on productivity are potentially heterogeneous. Other studies have come to similar conclusions. For instance, Dutcher (2012) provides experimental evidence that remote work for simple, repetitive tasks was associated with 10 percent lower productivity. In contrast, work for tasks requiring critical thinking and creativity was associated with 20 percent higher productivity. Likewise, Monteiro, Straume and Valente (2021) find remote work had a negative productivity association with firms primarily employing low-skilled workers. In contrast, remote work had significantly positive productivity effects for firms that undertake research and development activities.

Of course, the above analysis and conclusions require a number of caveats. First, as previously mentioned, working papers are just one dimension of output, as we do not include other research contributions such as publications, revisions, book chapters, and notes for the 12 regional banks. Based on our work with the Board economist webpages (which does include some of these items), the results would appear to be stronger and more significant if we were able to retrieve this data. Second, output related to policy work is not included yet also extremely important. Third, some economists use SSRN to release new papers, which we are not tracking. Fourth, if an economist chooses to publish in another branch's working papers, it will not be included in their time series, but this is rare. It is still included as a part of the overall system count. Fifth, all of the working papers and research contributions are treated equally, as we do not control for quality, which can be fairly subjective. And lastly, one view is that the pandemic was a unique time period in which there was a land-grab of papers on Covid along with more demand, and there might be a short-run/long-run trade-off as there was less time on conferences and less lunch with colleagues. To partially address this concern, we can exclude pandemic papers and can exclude 2020 and find that our results remain significant. We also show the results are very different when compared to the 2008 Global Financial Crisis, which was another land-grab event. With all that in mind, our results suggest that overall, remote work policies may have been associated with a significant boost in research output, with the lower half of the distribution experiencing the largest gains and collaboration also significantly increasing.

The structure of the paper is as follows. Section 2 describes the data and how it was collected along with summary statistics. Section 3 presents our regression results and some robustness checks, while Section 4 explores the effects on collaboration. Section 6 explores the theoretical macro implications of an exogenous increase in the time endowment and Section 7 concludes.

2 Data and Summary Statistics

2.1 Data construction

To better understand how research output may have been affected by WFH, we first had to come up with a proxy for output which we could measure before and during the pandemic. The proxy we used was number of working papers for the Fed System Regional Banks and a broader measure

of research contributions for the Board of Governors based on the economists' webpages. Working papers are a consistent and relatively parsimonious measure which persists across all of the Regional Banks and avoids issues associated with lag times related to the publication process. We collected publication dates for each working paper in addition to demographic data of the authors to construct the time series of each researcher. We accomplished this by going to each of the branch's websites to hand-collect the data. For the demographics of the authors, we consulted CVs, bios, and LinkedIn profiles. All of the information we use is based on publicly available data.

In addition to our time series, we also collect dates and associated number of coauthors for a comparison of collaboration before and during the pandemic. To create the time series for each of the researchers, we created a raw CSV file for each branch and added an entry for each time a working paper was produced. Each entry consists of working paper title, author name, estimated gender, PhD year, start/end date of employment, and branch. Once all the raw files for the twelve Regional Banks were complete for the years 2018 through 2022, we combined them into a larger raw file and ran that file through a custom program which outputs a time series for each author. The program also added in an authorID, whether or not the paper was a Covid-related paper based on title, and whether or not the paper was a revision. In total, there were 606 Branch authors, however a few were duplicates because they transferred from one branch to another during their career and would therefore only be counted once in the regressions.

For the Board, we used Board economist webpages that listed working papers, FEDS notes, publications and other research contributions dating back to 2018. The demographics data also comes from Board economist webpages and there was a total of 507 authors in our sample.

Working paper publication data for the Regional Banks is a relatively parsimonious measure that was feasible to collect given the time constraints for this study. Other measures, such as FEDS Notes, letters, publications, and others used in the case of the Board were not easily accessible for the Regional Banks. The rationale behind using 2018 through 2021 was (1) to keep the pre-pandemic and pandemic time samples closer in size and (2) to eliminate 2022 where some return to office policies began to take effect.

A number of caveats need to be mentioned with using working papers as the sole measure of research output, as we do for all of the Regional Banks. First, working papers are just one dimension of output: there are many other dimensions such as publications, revisions, book chapters, notes, and other research contributions that we were unable to track. Second, output related to policy work is also very important but we had no way of collecting this data. Third, our use of each Regional Banks' working paper series excludes those papers that are released on sites such as SSRN. And fourth, we take no stand on the quality of each research contribution and treat them all equally.

2.2 Summary Statistics

In this section, we present some of the summary statistics for this novel dataset. Figure 1 shows the percentage changes across all the Regional Banks. The Regional Banks experienced a roughly 20%

increase in output (average papers per quarter before versus during the pandemic), the Board's increase was over 30%, and the system's overall increase was around 26%. The summary statistics suggest that the number of working papers increased within the Regional Banks and that there could be a statistically significant increase in paper output per quarter per author. We see similarly large increases for research contributions per quarter per author at the Board. However, a more formal analysis using regressions and controls such as author fixed effects are required and that is what we do in the next section.

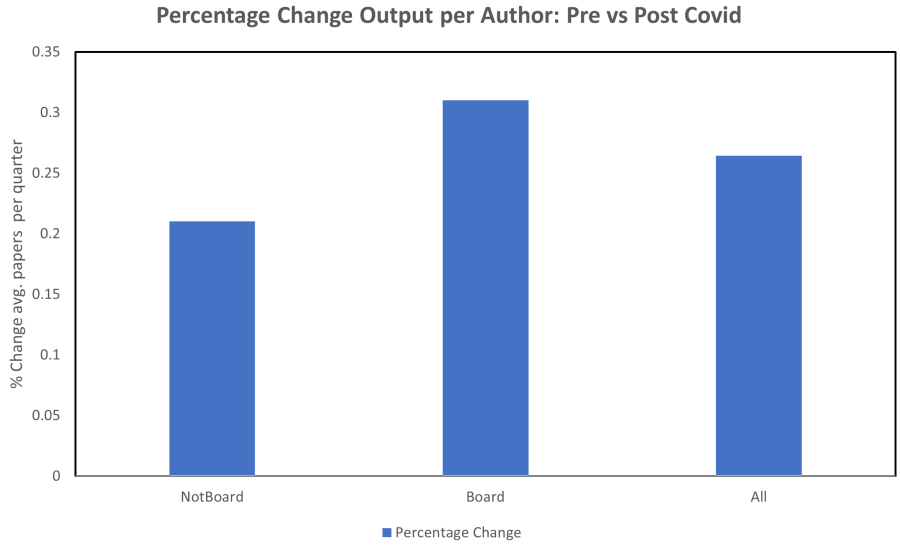


Figure 1: **Output per Paper Percentage Change Pre- vs Post-Covid**
Note: This figure shows the average percentage change in working papers per author from 2018q1-2020q1 to 2020q2-2021q4.

3 Results

The previous section provided evidence of increased output based on summary statistics. In this section, we use dynamic panel regressions to facilitate more formal analysis and the use of controls.

3.0.1 Poisson model

For the analysis that follows, we make use of both Poisson and linear regressions. We use both approaches because the underlying data represents counts of papers produced per quarter for each author. Count data tends to be zero-bounded and right-skewed. These features make standard linear regressions less than ideal for this type of analysis. For instance, Cohn, Liu and Wardlaw (2021) show that under a number of corporate finance applications, linear regressions may suffer from inherent biases that can cause them to have the wrong sign in expectation, in contrast to the Poisson regressions. Nonetheless, in our analysis, we include both types of regressions for robustness and most of our results are broadly consistent across the two types of approaches. In the few situations where there is disagreement, we tend to put more weight on the results coming

from the Poisson regression.

The Poisson regression assumes that the dependent variable follows a Poisson distribution, with density

$$f(y|x) = exp(-\mu(x))\mu(x)^y/y! \tag{1}$$

where $\mu(x) = E[y|x] = e^{x\beta}$.

In our baseline case, the conditional expectation takes the form $E[y|x] = e^{x\beta}$ or, equivalently,

$$log(E[y|x]) = x\beta \tag{2}$$

where y represents the number of papers per quarter for each author and x will often represent the indicator variable for the post-covid time period.

For the specifications where we allow author fixed effects, the conditional expectation is

$$E[y|x] = e^{(\alpha_i + x\beta)} = e^{\alpha_i}e^{x\beta} \tag{3}$$

where α_i is the fixed effect for author i. Note that the fixed effect is multiplicative as opposed to additive, as is the case in the linear model. As a result, the multiplicative fixed effect scales both the mean and the standard deviation, while an additive fixed effect only scales the mean. Cohn, Liu and Wardlaw (2021) argue the multiplicative fixed effects generally allow for better fit of the data, as the standard deviation of count variables is likely to scale with its mean.

3.0.2 Additional regression details

To improve our comparisons, we make some additional assumptions. First, we drop all researchers from the analysis that leave before the pandemic and also those researchers that arrive during the pandemic. Thus, our analysis is restricted to those researchers which were present before and during the pandemic. We accomplish this by dropping all authors who were not present the second quarter of 2020, which we use as the starting point for the post-covid period. WHAT DOES THIS MEAN? NOT EMPLOYED OR NOT PRODUCING PAPERS? Second, we drop all authors who do not produce any papers from 2018 through 2021, which is our period of interest.

The pre-covid time period is defined from the first quarter of 2018 through the first quarter of 2020. The post-covid time period is defined from the second quarter of 2020 through the fourth quarter of 2021. We choose these time periods because they are similar in length and we note that our results are robust to alternative ways of defining the two periods. This leads to a total of 16 time series observations

3.1 Main specification results

Table 1 shows the results of our main specification, where we regress output per author for each quarter against the covid indicator over our sample. The results are split into four specifications, with the left two columns representing the poisson regression and the right two columns being the

linear version. Each set of columns are further split into versions with and without author fixed effects.

We run the regressions for three groups: Panel A represents all Regional Banks excluding the Board, Panel B is the Board only, and Panel C is the combination of all Regional Banks and the Board. Upon noting that the coefficients for the poisson specification are akin to a percentage change, we can see that the results are largely consistent across all the specifications.[1] Each specification suggests there was an economically large and significant increase in output per author per quarter during the pandemic relative to the pre-covid time period.

Specifically, as shown in Panel A for the Regional Banks, we find a highly significant 17 to 19% increase in working papers per author for the post-covid time period. This is building on top of the 0.22 papers per quarter that were produced prior to the pandemic (or about 1 paper per year). Panel B shows that the increase was even larger for the Board, with a 27 to 28% increase in the number of research contributions. Recall that for the Board, we have a richer dataset that incorporates not just working papers, but also FEDS notes, along with book and journal publications. When we combine the entire system with the Board, we find a 23 to 24% increase that is highly significant.

These findings are in stark contrast to Jiang, Rösch, Liu and Tiu (2022), who focus on the top 1,000 finance and economics departments and find a significant negative effect on research output. Among many other reasons, it seems possible that the additional preparation required for remote teaching could be playing a crucial role in explaining the divergence in output between those in academia, and those in the Federal Reserve system, who did not face such costs.

3.2 Distributional implications

Given the large and significant increase in output, we next dive deeper into explaining which researchers experienced the greatest improvement. For this exercise, we split the sample into two halves based on output per author prior to the pandemic. We label the researchers that were in the upper half of the output per author distribution prior to the pandemic as a "Top Performer" and add this indicator to our main specification. In addition, we add an interactive term between covid and "Top Performer" to capture the additional effect on output that the upper half had during the pandemic.

As before, Table 2 shows the effect in the three panels across the Regional Banks, Board, and the entire system. For brevity, we focus our discussion on Panel C, which combines the entire system. The right column shows papers per quarter per author for the linear regression and is easiest to interpret for this exercise. We first interpret the "Top Perfomer" coefficient, which reflects the average papers per quarter per author for those in the upper half of the distribution. The coefficient of 0.308 plus the constant of 0.094 suggests the upper half are producing about 1.6 papers per year (0.4 x 4), while the bottom half is producing about 0.5 papers per year. The covid indicator captures the addtional effect for the lower half, while the sum for the covid plus

[1] To relate the coefficients for the constant, one must take the exponential for the poisson regression to compare it to the linear version.

Table 1: Quarterly Output per Author

	Poisson		Linear	
Fixed Effects	No	Yes	No	Yes
Panel A: Federal Reserve Regional Banks				
Covid	0.188***	0.170***	0.046***	0.041***
	(3.50)	(3.33)	(3.48)	(3.29)
Constant	−1.512***		0.221***	0.223***
	(−39.54)		(26.15)	(37.83)
Observations	6369	6369	6369	6369
Panel B: Board of Governors				
Covid	0.269***	0.282***	0.086***	0.091***
	(5.94)	(6.39)	(5.87)	(6.32)
Constant	−1.278***		0.279***	0.276***
	(−39.42)		(30.85)	(42.61)
Observations	7559	7559	7559	7559
Panel C: Combined				
Covid	0.233***	0.239***	0.066***	0.068***
	(6.70)	(7.13)	(6.64)	(7.03)
Constant	−1.376***		0.253***	0.252***
	(−55.51)		(40.34)	(56.32)
Observations	13928	13928	13928	13928

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

the "covid x Top Performer" represents the effect for the upper half of the distribution. We can see that the coefficient on covid of 0.130 nearly doubles the constant, suggesting that the lower half of the distribution nearly doubled their output over this time period. In contrast, the upper half of the distribution is little changed (0.130 - 0.125). Therefore, these results suggest that the upper half of the distribution continued to remain highly productive, while the bottom half substantially increased their output. This effectively reduced inequality between the two halves of the distribution.

This reduction in inequality between the two halves of the distribution is again in contrast to studies that focus on academia. In Jiang, Rösch, Liu and Tiu (2022) and Kruger, Maturana and Nickerson (2020), they found that the top departments were most responsible for any increase in output, which effectively increased inequality across researchers and universities.

3.3 Implications based on years since PhD

In this section, we break the sample into three age groups based on the years since PhD for each researcher. The youngest cohort are those that have completed a PhD within the past 8 years. We choose this threshold to line up with previous studies, which focus on those below 35 years of age. The middle cohort are those between 8 and 22 years since completion of the PhD. And the oldest cohort are those 22 years and beyond. Again, these thresholds are chosen to be consistent with previous studies that focused on ages 35 to 49 and 50 and over.

We can see from Table 3 Panel C that the interaction term for "Covid x Under 8" is significant and positive. The poisson specifications suggests there was a 16% addtional boost for this cohort above and beyond the rest of the researchers. The rest of the researchers experienced about a 20% boost, as indicated by the coefficient on Covid. This implies the youngest cohort experienced close to a 35% increase in output over this time period.

When we move to the middle cohort, we see a fairly different picture. As shown in Table 4 Panel C, those with a PhD from 8 to 22 years ago significantly underperformed the rest of the cohort. However, note that the sum of "Covid" and "Covid x 8 to 22" (0.340 - 0.176) is still positive and significant. Thus, while this cohort produced relatively less than the other cohorts, it still significantly increased its output during the pandemic.

Lastly, when we move to the oldest cohort, we again see some improvement in Table 5, although primarily at the Board. At the Board, as shown in Panel B, we can see that the "Covid x 22 Plus" variable is highly significant and indicating close to a 23% additional boost above the rest of the cohorts, with a sum effect for "Covid" plus "Covid x 22 Plus" of about 45%.

Overall, these results suggest that all cohorts significantly increased output, with the youngest and oldest cohorts gaining the most. These findings are largely consistent with the studies that focused on professors. The relatively lower output of those in the middle cohort has been cited as potentially due to those individuals being more likely to have younger children and may have faced increased difficulty with child rearing during the pandemic.

Table 2: Quarterly Output per Author: Top Half of Distribution Effect

	Poisson	Linear
Panel A: Federal Reserve Regional Banks		
Covid	0.678***	0.102***
	(7.13)	(6.87)
Top Performer	1.202***	0.244***
	(14.27)	(14.49)
Covid x Top Performer	−0.742***	−0.124***
	(−6.48)	(−4.72)
Constant	−2.254***	0.105***
	(−31.13)	(13.80)
Observations	6369	6369
Panel B: Board of Governors		
Covid	1.049***	0.156***
	(10.95)	(10.71)
Top Performer	1.653***	0.356***
	(19.22)	(21.99)
Covid x Top Performer	−0.984***	−0.127***
	(−9.08)	(−4.63)
Constant	−2.475***	0.084***
	(−31.23)	(12.62)
Observations	7559	7559
Panel C: Combined		
Covid	0.864***	0.130***
	(12.87)	(12.46)
Top Performer	1.451***	0.308***
	(24.30)	(26.10)
Covid x Top Performer	−0.854***	−0.125***
	(−10.94)	(−6.53)
Constant	−2.361***	0.094***
	(−44.15)	(18.69)
Observations	13928	13928

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

Table 3: Quarterly Output per Author: Under 8 Years Since PhD Effect

	Poisson	Linear
Panel A: Federal Reserve Regional Banks		
Covid	0.161***	0.039***
	(2.70)	(2.68)
Under 8	−0.109	−0.023
	(−0.97)	(−1.01)
Covid x Under 8	0.159	0.037
	(1.11)	(1.09)
Constant	−1.495***	0.224***
	(−36.40)	(24.33)
Observations	6369	6369
Panel B: Board of Governors		
Covid	0.231***	0.073***
	(4.60)	(4.55)
Under 8	−0.016	−0.004
	(−0.18)	(−0.18)
Covid x Under 8	0.195*	0.074*
	(1.67)	(1.87)
Constant	−1.275***	0.279***
	(−36.12)	(28.32)
Observations	7559	7559
Panel C: Combined		
Covid	0.202***	0.057***
	(5.25)	(5.20)
Under 8	−0.051	−0.013
	(−0.74)	(−0.75)
Covid x Under 8	0.160*	0.048*
	(1.75)	(1.85)
Constant	−1.368***	0.255***
	(−50.95)	(37.24)
Observations	13928	13928

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

Table 4: Quarterly Output per Author: 8 to 22 Years Since PhD Effect

	Poisson	Linear
Panel A: Federal Reserve Regional Banks		
Covid	0.201***	0.047***
	(2.62)	(2.61)
8 to 22	0.074	0.016
	(0.97)	(0.97)
Covid x 8 to 22	−0.022	−0.002
	(−0.20)	(−0.09)
Constant	−1.549***	0.212***
	(−27.74)	(17.90)
Observations	6369	6369
Panel B: Board of Governors		
Covid	0.457***	0.110***
	(6.37)	(6.34)
8 to 22	0.669***	0.181***
	(9.91)	(10.07)
Covid x 8 to 22	−0.288***	−0.042
	(−3.13)	(−1.43)
Constant	−1.663***	0.190***
	(−30.38)	(18.27)
Observations	7559	7559
Panel C: Combined		
Covid	0.340***	0.081***
	(6.50)	(6.47)
8 to 22	0.428***	0.107***
	(8.50)	(8.55)
Covid x 8 to 22	−0.176**	−0.026
	(−2.52)	(−1.32)
Constant	−1.610***	0.200***
	(−41.16)	(25.57)
Observations	13928	13928

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

Table 5: Quarterly Output per Author: 22 Plus Years Since PhD Effect

	Poisson	Linear
Panel A: Federal Reserve Regional Banks		
Covid	0.213***	0.053***
	(3.28)	(3.27)
22 Plus	−0.020	−0.005
	(−0.25)	(−0.25)
Covid x 22 Plus	−0.084	−0.023
	(−0.72)	(−0.82)
Constant	−1.505***	0.222***
	(−32.13)	(21.35)
Observations	6369	6369
Panel B: Board of Governors		
Covid	0.223***	0.087***
	(4.40)	(4.36)
22 Plus	−0.835***	−0.196***
	(−10.32)	(−11.90)
Covid x 22 Plus	0.229**	−0.001
	(2.11)	(−0.02)
Constant	−1.058***	0.347***
	(−29.71)	(28.06)
Observations	7559	7559
Panel C: Combined		
Covid	0.205***	0.066***
	(5.11)	(5.07)
22 Plus	−0.476***	−0.110***
	(−8.38)	(−9.07)
Covid x 22 Plus	0.084	−0.006
	(1.07)	(−0.29)
Constant	−1.235***	0.291***
	(−43.24)	(35.02)
Observations	13928	13928

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

3.4 Implications based on gender

We also explored whether or not there were significant differences between males and females. Previous studies have found there was a significant difference, with females producing less than males over this time period. In contrast, as shown in Table 6, we find that there was no significant difference between males and females in terms of output across the entire system, as evidenced by the low t-stats for the "Covid x Female" indicator variable. Moreover, the coefficients are very close to zero.[2]

3.5 Robustness checks

3.5.1 Excluding the year 2020

One potential concern with our results is that perhaps we are capturing a spike in 2020 that quickly reverted. To partially address this concern, we remove the year 2020 from our sample and determine whether our results continue to hold. Table 7 shows the significance continues to hold, with an effect that remains economically large (11 to 13 %) and is in line with studies such as Bloom, Liang, Roberts and Ying (2015), although their study focuses on hybrid and not fully remote work.

3.5.2 Excluding "Covid" and "Pandemic" papers

In this section, we exclude papers that have the words "Covid" and "Pandemic" in the title. It's possible that the increase in papers is less about WFH and more about the emergence of a new research topic. In table 8, we see that the increase remains significant and sizable. Upon excluding all papers that mention these terms in the title, the increase in output remains near 10%.

3.5.3 Comparison to Global Financial Crisis

As previously mentioned, the gains could be driven more by the presence of new research ideas. While plausible, this view rests on the assumption that the constraining factor on researchers prior to the pandemic was not time, but a limited number of research ideas. We view the period around the Global Financial Crisis as another event in which new research ideas would emerge, yet importantly, there was no change in remote work policies over this time period. Thus, this period could serve as a good comparison.

If we compute the average number of working papers produced per year from 2006 to 2008 and compare it to 2009 to 2010, we find it declined from 397 to 394.5. Figure 2 shows a breakdown conducted by branch for the percentage change in output pre and post global financial crisis, and a similar figure is provided for the current episode. We can see that many more Regional Banks experienced declines in research output between the two time periods, when compared to pre- and post-pandemic. Thus, a takeaway is that we didn't observe a large increase in research output around the GFC, in contrast to the pandemic.

[2]We find that the pre-pandemic negative and significant coefficient for the Board is no longer significant if we just remove a single author, indicating this observed significance is fragile.

Table 6: Quarterly Output per Author: Female Effect

	Poisson	Linear
Panel A: Federal Reserve Regional Banks		
Covid	0.202***	0.049***
	(3.37)	(3.34)
Female	0.041	0.009
	(0.42)	(0.41)
Covid x Female	−0.066	−0.016
	(−0.49)	(−0.48)
Constant	−1.520***	0.219***
	(−35.91)	(23.62)
Observations	6369	6369
Panel B: Board of Governors		
Covid	0.276***	0.092***
	(5.26)	(5.20)
Female	−0.125*	−0.034*
	(−1.70)	(−1.75)
Covid x Female	−0.023	−0.019
	(−0.23)	(−0.59)
Constant	−1.241***	0.289***
	(−32.93)	(26.53)
Observations	7559	7559
Panel C: Combined		
Covid	0.240***	0.069***
	(6.06)	(6.00)
Female	−0.037	−0.009
	(−0.62)	(−0.63)
Covid x Female	−0.029	−0.011
	(−0.35)	(−0.49)
Constant	−1.367***	0.255***
	(−48.40)	(35.41)
Observations	13928	13928

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

Table 7: Quarterly Output per Author: 2020 Excluded

	Poisson		Linear	
Fixed Effects	No	Yes	No	Yes
Combined				
Covid	0.127***	0.109***	0.037***	0.032***
	(3.03)	(2.68)	(2.98)	(2.65)
Constant	−1.296***		0.274***	0.275***
	(−49.32)		(38.05)	(65.84)
Observations	9383	9383	9383	9383

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

Table 8: Quarterly Output per Author: Covid Papers Excluded

	Poisson		Linear	
Fixed Effects	No	Yes	No	Yes
Combined				
Covid	0.102***	0.109***	0.027***	0.029***
	(2.84)	(3.12)	(2.82)	(3.10)
Constant	−1.377***		0.252***	0.252***
	(−55.51)		(40.32)	(58.62)
Observations	13928	13646	13928	13928

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

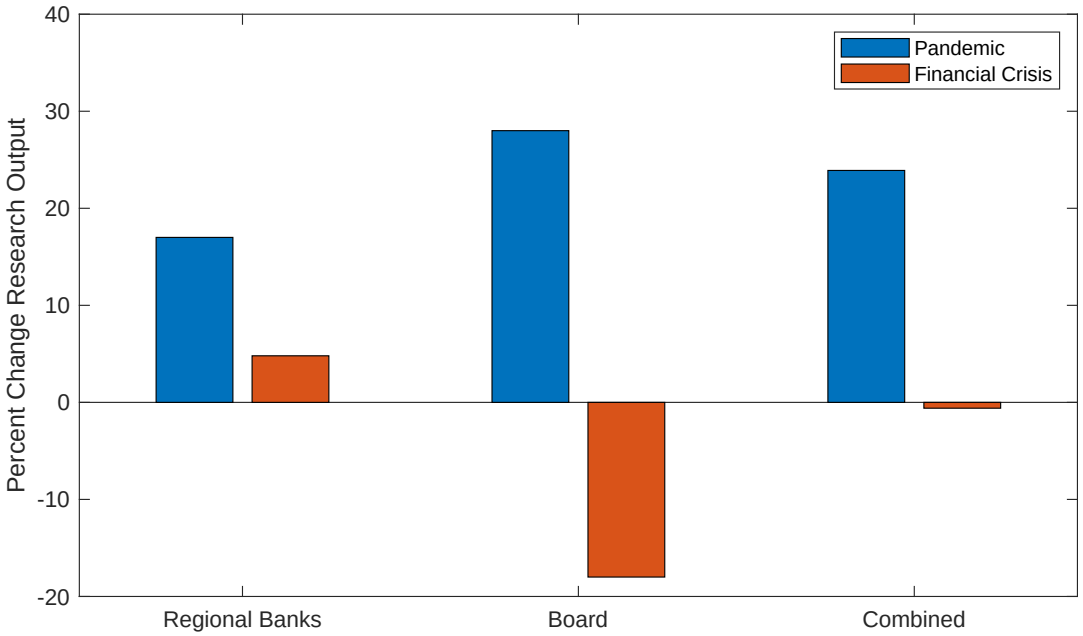


Figure 2: **Percentage Change in Output Comparison to Global Financial Crisis**
Note: The figure shows the percentage change in output for 2005 to 2008 (pre) vs 2009 to 2010 (post) global financial crisis (orange) and pre vs during the pandemic (blue).

4 Collaboration

We can also evaluate whether collaboration increased over the pandemic. One way to do that is to keep track of authors per paper. Below are summary statistics for pre vs post pandemic, plotted for the Regional Banks, in addition to the Board, and the combined system.

Figure 3 shows the percentage changes that confirms the previous figures. Most of the Regional Banks saw an increase in collaboration as defined by authors per paper, with the whole system producing about a 10% increase.

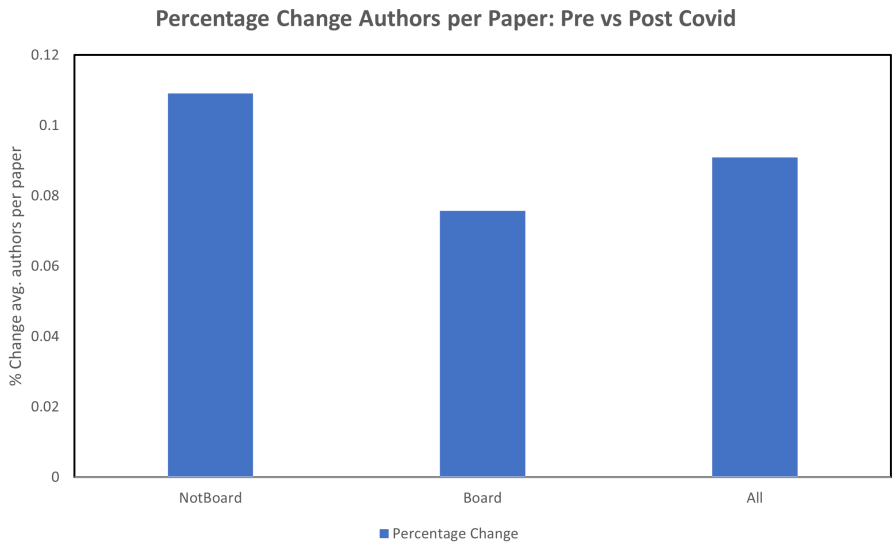


Figure 3: **Percentage Change in Collaboration: Authors per Paper Pre vs Post Covid**
Note: The pre covid time period is 2018q1 to 2020q1 and the post covid time period is 2020q2 to 2021q4.

To check if this increase is significant we run regressions while also incorporating a time trend. Table 9 shows that whether or not we include a time trend, the increase in collaboration is significant and about 10%.

Table 9: Collaboration: Authors per Paper

	Poisson	Linear	Poisson	Linear
Combined				
Covid	0.0713***	0.224***	0.105***	0.331***
	(4.07)	(4.04)	(3.92)	(3.93)
Trend Effect			−0.0184	−0.0573
			(−1.56)	(−1.56)
Constant	1.111***	3.038***	1.126***	3.083***
	(97.51)	(87.74)	(73.99)	(65.40)
Observations	4606	4606	4606	4606

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

5 Micro-economic Mechanism [PRELIMINARY]

In this section, we present the principal-agent model in its most basic form, with the goal of showing that pre-existing differences in the use of incentive contracts across different occupations

can generate both negative and positive productivity outcomes with respect to remote work.

We start with the case in which the effort of the agent cannot be perfectly observed. This would likely coincide with the economist regardless of work environment and the call center worker in the remote work environment. We assume that the worker or agent chooses effort e. Output is defined as a function of effort and some error term

$$y = e + \varepsilon \tag{4}$$

where $\mathbb{E}[\varepsilon] = 0$. The risk neutral principal or firm pays a salary w to the agent, which is a function of output:

$$w = a + by = a + be + b\varepsilon \tag{5}$$

The principal maximizes expected profits

$$\mathbb{E}[\pi] = \mathbb{E}[y - w(y)] = e - \mathbb{E}[w(y)] \tag{6}$$

and the risk averse agent ($U' > 0$ and $U'' < 0$) maximizes expected utility by choosing effort e

$$\mathbb{E}[U(w(e + \varepsilon))] - c(e) \tag{7}$$

where $c(e)$ is a convex function representing the cost of effort ($c'(e) > 0$, $c''(e) > 0$) for all e.

Solving the principal-agent problem involves backward induction. The first step is to determine the optimal effort of the worker for a given wage contract. For ease of derivation, we assume the following functional forms

$$U(w) = -exp(-\gamma w) \tag{8}$$

and $\varepsilon \sim N(0, \sigma^2)$. This implies that

$$\mathbb{E}[U(a + be + b\varepsilon))] = a + be - \frac{\gamma}{2} b^2 \sigma^2 \tag{9}$$

The cost function takes the following form

$$c(e) = \frac{\kappa e^2}{2} \tag{10}$$

The agent solves the following problem

$$\max_e \mathbb{E}[U(w))] - c(e) \tag{11}$$

where the solution is

$$e^* = \frac{b}{\kappa} \tag{12}$$

Intuitively, this suggests the agent will provide more effort the more the wage loads on output, b. Likewise, the agent will provide less effort with greater cost of effort, κ.

The second step is to make sure the agent is willing to work for the principal by ensuring the individual rationality condition holds.

$$\mathbb{E}[U(w))] - c(e) \geq 0 \tag{13}$$

If we substitute the solution for e^* we get

$$a + be^* - \frac{\gamma}{2}b^2\sigma^2 - c(e^*) = 0 \tag{14}$$

and this holds with equality because the principal is maximizing profit.

The firm or principal now wishes to maximize profits subject to the optimal effort decision and individual rationality condition

$$\begin{aligned} \max_{a,b} \quad & \mathbb{E}[\pi] = e - \mathbb{E}[w(y)] = e - a - be \\ s.t. \quad & e^* = \frac{b}{\kappa} \\ & a^* = -be^* + \frac{\gamma}{2}b^2\sigma^2 + \frac{\kappa e^{*2}}{2} \end{aligned}$$

The first order condition is

$$0 = 1 - \gamma c'(e)\sigma^2 c''(e) - c'(e) \tag{15}$$

which implies

$$e^* = \frac{1}{\kappa}\frac{1}{1+\gamma\sigma^2\kappa} \tag{16}$$

and

$$b^* = \kappa e^* = \frac{1}{1+\gamma\sigma^2\kappa} \tag{17}$$

In words, this implies that the optimal effort e^* declines with greater risk aversion γ and greater uncertainty σ^2. Likewise, the optimal wage loading on output, b^*, is strictly less than one if there is any uncertainty and the worker is risk averse. The intuition is that risk averse worker gets less utility when the wage is uncertain, as is the case if high effort may never-the-less produce low output. Thus to induce the same effort, the firm must pay a higher average cost when only output and not effort is observable. The profit maximizing firm therefore finds it optimal to buy less effort.

What about the on-site call center worker, where effort is observable?

Here we can solve the problem again but assume there is no uncertainty. The principal offers a flat wage this time as long as the agent chooses effort e^*

$$w = a \tag{18}$$

which is in contrast to the case with uncertainty ($w = a + by$).

The worker's individual rationality condition is now

$$a - c(e) \geq 0 \tag{19}$$

Given the principal or firm wants to minimize pay, it sets

$$a^* = c(e^*) \tag{20}$$

As before, the firm maximizes profits subject to the optimal effort decision and individual rationality condition

$$\max_a \mathbb{E}[\pi] = e - \mathbb{E}[w(y)] = e - a^* = e - c(e^*) = e - \frac{\kappa e^2}{2} \tag{21}$$

And the solution implies

$$e^*_{FirstBest} = \frac{1}{\kappa} \tag{22}$$

This level of effort for the in-office worker, $\frac{1}{\kappa}$, is greater than $\frac{b}{\kappa}$ for the remote worker. This provides the theoretical framework for why the call center worker, when moving from the low monitoring cost setting to high monitoring cost setting, will have lower effort.

In contrast, the academic or economist is likely to be already in the output-based constrained-efficient incentive contract, regardless of whether it is in-office or remote. That's because research papers, for example, entail high monitoring costs as they can take years to write and follow numerous paths to completion regardless of the setting in which they are produced. Therefore, unlike the call center worker, there is no shift in the structure of the contract when moving to remote. Without a change in the nature of the contract, effort costs become the dominant mechanism affecting worker output in moving to remote, the largest of which could be those associated with commuting. By reducing these costs, which in the model would entail a lower κ, the worker is willing to produce more for a given wage, which translates into greater output.

Finally, with respect to heterogeneity within an occupation such as academics, the dominant mechanism is likely to be different effort costs associated with remote work, or a different κ. It's plausible that the costs of effort were reduced for those focused on research when they were remote, while those positions with greater focus on teaching faced greater costs due to changes in curriculum.

Overall, we have been able to appeal to a standard principal-agent model to rationalize how certain professions could potentially have negative effects of remote work while others could have positive effects. In the next section, we broaden our theoretical analysis to explore the potential aggregate implications of remote work in a macroeconomic model.

6 Theoretical Aggregate Implications

In this section, we consider whether the increased research output can be motivated with an economic mechanism and what this may imply for other macroeconomic aggregates. Specifically, we

use a standard New-Keynesian model with endogenous growth to determine the potential effects of an exogenous increase in the time endowment. This exercise seems to be particularly relevant given the findings in Bloom, Han and Liang (2022). They note that the average employee saves about 70 minutes a day by avoiding having to commute and prepare for work.

Model and calibration. We use a New-Keynesian endogenous growth model similar to Kung (2015) as the laboratory to study the theoretical response of productivity, economic growth, inflation, and interest rates to an exogeous increase in the time endowment. This model contains a representative agent with recursive preferences. On the production side, intermediate goods firms are subject to adjustment costs in price-setting, physical capital, and R&D. Firms can upgrade their technology by investing in R&D and there are spillover effects to aggregate productivity. A final goods firm aggregates intermediate goods with a CES technology. Monetary policy sets the nominal interest rate according to a Taylor-type rule responding to inflation and output growth. There are three shocks in this model: a transitory shock to the level of productivity, a shock to the volatility of the transitory productivity shock, and a monetary policy shock. Kung (2015) demonstrates the model is able to match a wide range of macroeconomic and asset pricing moments. Appendix B provides full details of the model and discusses parameter values and model moments.

Positive time endowment shock. For our purposes, we will be simulating an exogenous shock to the time endowment. The time endowment enters several equilibrium conditions that make up the model, such as the household's intratemporal and intertemporal first order conditions. At the optimum, the intratemporal equation equates the real wage to the marginal rate of substitution between leisure and consumption as shown below

$$\frac{W_t}{P_t} = \frac{\tau C_t}{\bar{L} - L_t} \tag{23}$$

where τ is the parameter governing how much weight leisure receives in the consumption-leisure bundle $C_t(\bar{L} - L_t)^{\tau}$. An exogenous increase in $\bar{L}$ is very similar to an intratemporal preference or labor supply shock (i.e. a shock to τ).

However, a key difference is the response of leisure: with the intratemporal preference shock, the time endowment remains unchanged, and thus leisure must fall if the time spent on labor rises. In contrast, for the time endowment shock, leisure and labor can both rise, which will lead to an unambiguous increase in the consumption-leisure bundle, an important component of the household's utility function.

For the impulse response functions that follow, we simulate a persistent increase in the time endowment, where we assume a one percent increase in the time endowment. Given that the typical model targets households working a third of the time, the total endowment is typically associated with 120 hours a week, 40 of which are devoted to labor. A one percent increase in the endowment is roughly an additional hour per week, which is close to the estimates of the time saved for WFH across all people, even those that never work remotely, according to Aksoy, Barrero, Bloom, Davis,

Dolls and Zarate (2023).

Simulated dynamics. Figure 4 shows in the top row that of the 1% increase in the time endowment, about two-thirds goes to leisure and one-third goes to labor. Again, this is not far from the findings of Aksoy, Barrero, Bloom, Davis, Dolls and Zarate (2023), who find those who WFH devote 40 percent of their time savings to labor.

The increased labor supply translates to higher output and consumption growth, along with additional R&D investment. The latter increase, which is associated with idea accumulation and positive spillovers to aggregate productivity, leads to the rise in productivity growth shown in the third row for the right column.

The increased labor supply is also associated with lower real wages and lower marginal costs (both not shown), and this translates to close to 50 basis points lower inflation according to the simulation. With monetary policy responding to inflation based on a standard Taylor-type rule, the nominal short rate also declines, although not as much due to the presence of the inertia coefficient and response to output growth. The persistent decline in the nominal risk-free rate ultimately leads to a persistent rise in the 10 year minus 3-month yield spread, which coincides with the positive expected output growth, replicating the positive empirical association between yield spreads and expected growth.

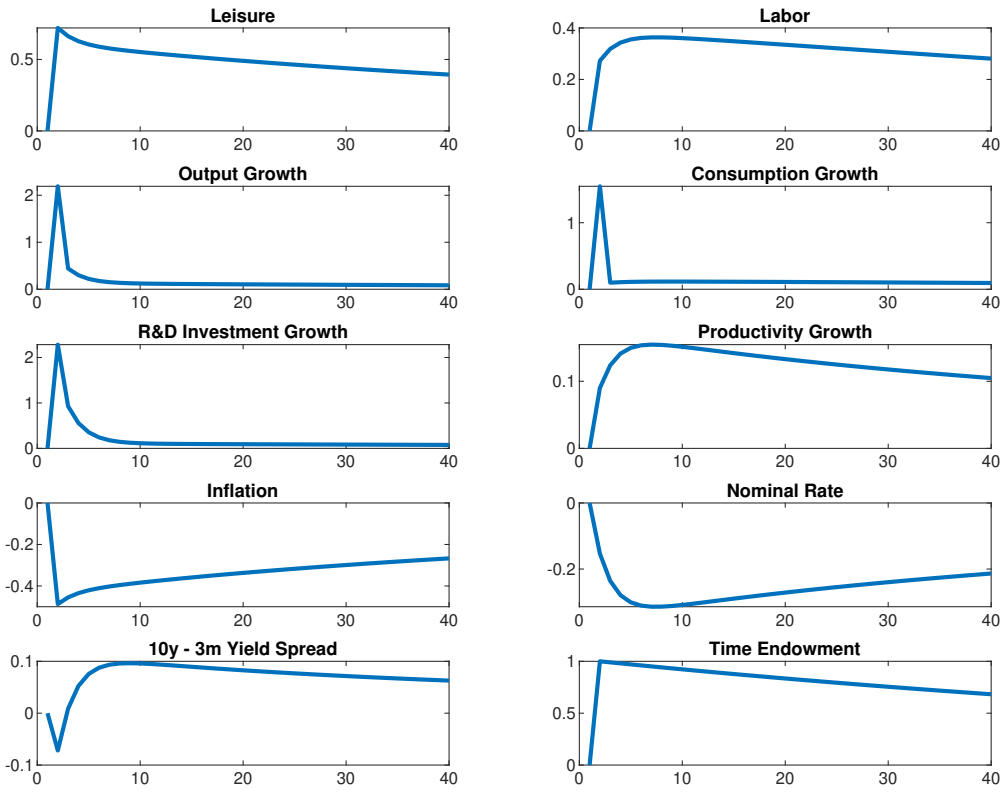


Figure 4: **Macroeconomic Responses to a Positive Time Endowment Shock**

Note: The impulse responses show the effects of a 1 percent increase in the time endowment. All units are annualized and in percentage deviation from steady state.

RTO: Negative time endowment shock. Just as one can simulate a positive time endowment shock that may be associated with the shift to WFH, one can also simulate a negative time endowment shock with the shift towards the return-to-office. It stands to reason that any shift towards the return-to-office will be associated with increased commute times and a negative shock to the time endowment. According to the theoretical model, this type of shock is likely to be associated with higher inflation, a higher nominal short rate, a lower yield spread, and lower productivity growth.

The potential effects described above are based on a theoretical model. Below we document what has actually happened to aggregate productivity over the past several years. While some could argue that the movements in observed aggregate productivity are purely due to composition effects coming from changes to the labor force, an alternative explanation could be related to the initial expansion of WFH along with the subsequent increase in RTO. Figure 5 shows a marked increase in the level of productivity early in the pandemic, that stays elevated through the end of 2021. However, as RTO became more prominent in 2022, we start to see a decline back to trend. The bottom plot shows a similar dynamic, as the four quarter change in aggregate productivity turns negative as internet searches regarding RTO jumped considerably. The takeaway here is that although much of this could be chalked up to changes in the composition of the workforce over this

time period, the rise and fall in productivity are consistent with the predictions coming from the theoretical model in which the time endowment is exogenously increased and then falls.

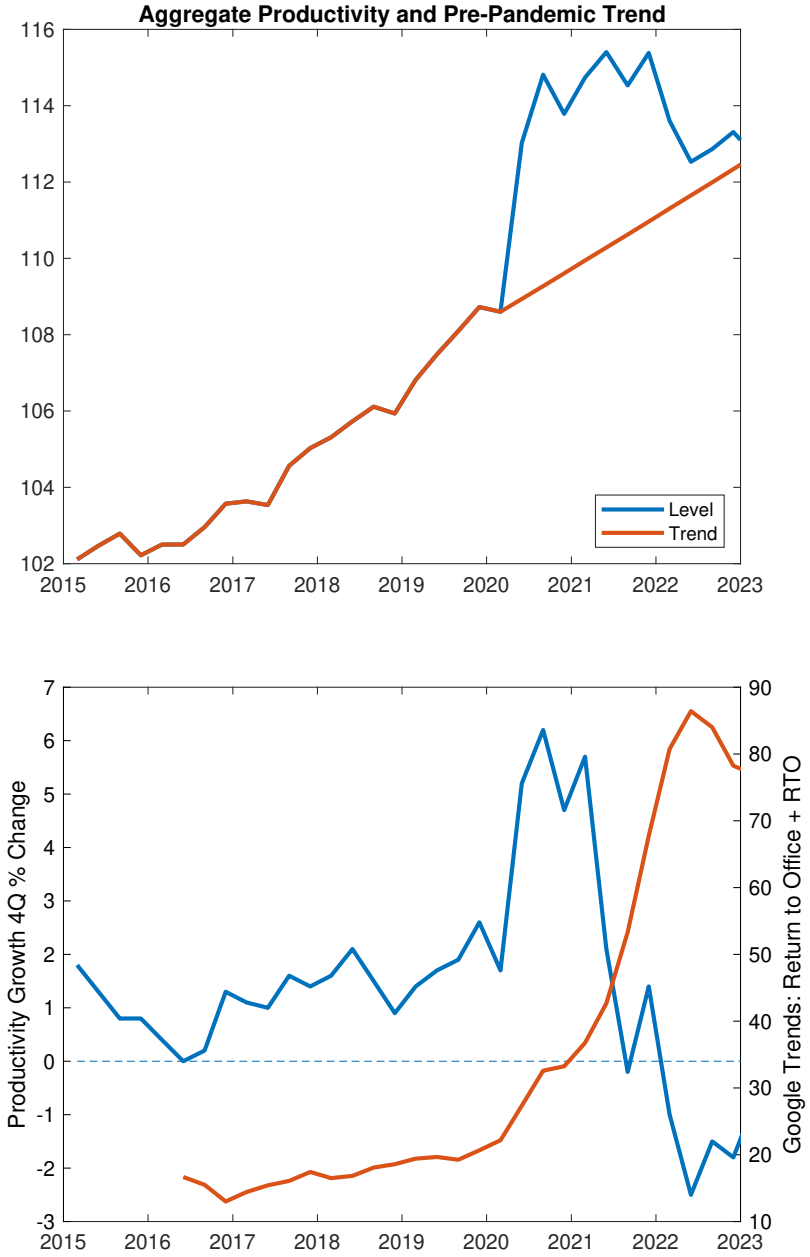


Figure 5: **Aggregate Productivity Level and Trends**

Note: The top plot shows the aggregate productivity level (blue) according to the BLS. Specifically, the series titled "Index/Level and Office of Productivity and Technology and Productivity : Nonfarm Business". The trend line (orange) is based on the average growth since 2015. The bottom plot shows the four-quarter change in the aggregate productivity level versus a 12-month moving average of the Google trends for the terms Return to Office and RTO.

7 Conclusion

The effects and consequences of remote work are playing out in real-time. How fully remote work affects output and productivity has important macroeconomic implications, as increased productivity tends to reduce inflation. We find there was a large and significant increase in research output over the pandemic that was largely driven by the lower half of the pre-pandemic output distribution. This fact led to a decrease in inequality of research output across researchers. There was no significant difference between males and females, in contrast to previous studies focusing on university professors, and the younger and older cohorts seemed to benefit the most. Moreover, collaboration as measured by authors per paper significantly increased.

Some of the reasons that remote work may have increased output have already been highlighted by other studies such as Bloom, Han and Liang (2022). For instance, they note that the average employee saves about 70 minutes a day by avoiding having to commute and prepare for work, which is split into both additional work and leisure. In addition, home working is often better for individual focused activities like coding or writing papers because it is usually quieter. The greater time flexibility and the ability to control ambient workspace such as clothing, layout, and ventilation are also factors that have been cited. Lastly, Choudhury, Foroughi and Larson (2021) theorize that those that self-select into remote work will tend to experience greater satisfaction and utility, and will exert greater productivity-enhancing effort in appreciation of this nonpecuniary benefit.

To better understand our empirics and how they relate to existing findings, we take two theoretical approaches. We first show that variation in productivity outcomes is in fact consistent with the predictions of a standard principal-agent model once we acknowledge pre-existing differences in the use of incentive contracts across different occupations. We then broaden our analysis by using theoretical simulations from a New Keynesian endogenous growth model in which there is a positive shock to the time endowment. In this scenario, we find that households optimally choose to split the increased time between labor and leisure. The additional labor supply contributes to higher output, consumption, and R&D investment, which feeds into higher aggregate productivity while putting downward pressure on inflation and the nominal risk-free rate. Subsequently, a return-to-office policy that reduces the time endowment, would have the opposite effects. Our findings suggest that the observed rise and fall in aggregate productivity over the last few years are not inconsistent with the predictions coming from the theoretical model in which the time endowment is exogenously increased and then falls.

Overall, while our findings are indeed compelling, it's important to avoid over-interpreting or overly generalizing these results. We leave for future research the deeper look into whether research output changes have occurred at other central banks like the European Central Bank (ECB), or similar institutions like the International Monetary Fund (IMF).

References

Aksoy, Cevat Giray, Jose Maria Barrero, Nicholas Bloom, Steven J Davis, Mathias Dolls, and Pablo Zarate (2023) "Time savings when working from home,"Technical report, National Bureau of Economic Research.

Atkin, David, Antoinette Schoar, and Sumit Shinde (2023) "Working from home, worker sorting and development,"Technical report, National Bureau of Economic Research.

Barrero, José María, Nicholas Bloom, and Steven J Davis (2023) "The evolution of work from home," *Journal of Economic Perspectives*, 37 (4), 23–49.

Bloom, Nicholas, Ruobing Han, and James Liang (2022) "How Hybrid Working From Home Works Out,"Technical report, National Bureau of Economic Research.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying (2015) "Does working from home work? Evidence from a Chinese experiment," *The Quarterly Journal of Economics*, 130 (1), 165–218.

Choudhury, Prithwiraj, Cirrus Foroughi, and Barbara Larson (2021) "Work-from-anywhere: The productivity effects of geographic flexibility," *Strategic Management Journal*, 42 (4), 655–683.

Cohn, Jonathan B, Zack Liu, and Malcolm Wardlaw (2021) "Count data in finance," *Available at SSRN 3800339*.

Dutcher, E Glenn (2012) "The effects of telecommuting on productivity: An experimental examination. The role of dull and creative tasks," *Journal of Economic Behavior & Organization*, 84 (1), 355–363.

Emanuel, Natalia and Emma Harrington (2021) "'Working'remotely? Selection, treatment and the market provision of remote work,"Technical report, working paper, 9 April.

Jiang, Yuxiang, Dominik Rösch, Ruijie Liu, and Cristian Ioan Tiu (2022) "COVID-19 and the illusion of productivity," *Available at SSRN 4086866*.

Kruger, Samuel, Gonzalo Maturana, and Jordan Nickerson (2020) "How Has COVID-19 Impacted Research Productivity in Economics and Finance?" *Available at SSRN 3745226*.

Kung, Howard (2015) "Macroeconomic linkages between monetary policy and the term structure of interest rates," *Journal of Financial Economics*, 115 (1), 42–57.

Monteiro, Natalia P, Odd Rune Straume, and Marieta Valente (2021) "When does remote electronic access (not) boost productivity? Longitudinal evidence from Portugal," *Information Economics and Policy*, 56, 100923.

Appendix

A Revisions

One issue with the approach taken in this study is we do not account for revisions, which plays an important role in the research process. To check whether this may be important for our results, we used the Philadelphia Regional Bank as a test case and compared the results to the case where we include revisions.

Table A.1 shows that the effect on output becomes stronger when we include revisions. If this example that we use here is consistent with the rest of the Regional Banks, it suggests we may be understating the overall effect of remote work on output, and that if we were to include revisions for all Regional Banks, the effect would be stronger.

Table A.1: Quarterly Output per Author: Philadelphia Revisions

	Poisson		Linear	
Fixed Effects	No	Yes	No	Yes
Panel A: With Revisions				
Covid	0.221*	0.246*	0.053*	0.060*
	(1.76)	(1.90)	(1.76)	(1.90)
Constant	−1.536***		0.215***	0.212***
	(−16.47)		(10.72)	(14.07)
Observations	1202	1202	1202	1202
Panel B: Without Revisions				
Covid	0.119	0.139	0.026	0.030
	(0.91)	(1.05)	(0.91)	(1.04)
Constant	−1.597***		0.203***	0.200***
	(−16.90)		(10.58)	(14.52)
Observations	1202	1202	1202	1202

Note: t-statistics in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and clustered by author.

B The Model

In this section, we present our baseline New Keynesian endogenous growth model, which is similar to the framework in Kung (2015).

B.1 Households

The representative household has recursive utility over consumption C_t and leisure $\bar{L} - L_t$. The value function the representative household is seeking to maximize is

$$V_t = \left[(1-\beta) \left(C_t (\bar{L} - L_t)^{\tau} \right)^{1-\psi} + \beta \mathbb{E}_t \left[V_{t+1}^{1-\gamma} \right]^{\frac{1-\psi}{1-\gamma}} \right]^{\frac{1}{1-\psi}}, \tag{B.1}$$

subject to the budget constraint:

$$P_t C_t + \frac{B_{t+1}}{R_{t+1}} = D_t + W_t L_t + B_t \tag{B.2}$$

where β is the time discount factor, γ is relative risk aversion, τ is the weight on leisure in the utility function, and ψ is the inverse of intertemporal elasticity of substitution (IES). B_{t+1} denotes the quantity of a one-period to maturity zero coupon bond issued at time t and maturing at time $t+1$, and R_{t+1} is the gross one-period nominal interest rate set at time t by the monetary authority. D_t is the nominal dividend income received from the intermediate firms and L_t is labor hours supplied by the household and $\bar{L}$ is the agent's time endowment. Lastly, P_t is the price level of the final consumption good at time t.

The household's intertemporal constraint is

$$1 = E_t \left[M_{t+1} \frac{P_t}{P_{t+1}} \right] R_{t+1} \tag{B.3}$$

where the real stochastic discount factor is

$$M_{t+1} = \beta \left(\frac{C_{t+1}(\bar{L} - L_{t+1})^{\tau}}{C_t (\bar{L} - L_t)^{\tau}} \right)^{1-\psi} \left(\frac{C_{t+1}}{C_t} \right)^{-1} \left(\frac{V_{t+1}^{1-\gamma}}{E_t [V_{t+1}^{1-\gamma}]} \right)^{\frac{\psi-\gamma}{1-\gamma}} \tag{B.4}$$

The household's intratemporal constraint is

$$\frac{W_t}{P_t} = \frac{\tau C_t}{\bar{L} - L_t} \tag{B.5}$$

Note that for the purposes of this paper, $\bar{L}$, the time endowment, will be exognously increased/decreased and thus can be time-varying.

B.2 Firms

There is a continuum of monopolistic intermediate good producers in the economy. Each firm employs labor $L_{t,j}$ from households and rents physical capital $K_{t-1,j}$, along with R&D capital $N_{i,t}$, to produce good $X_{t,j}$. Firm j follows a Cobb-Douglas production function of the following form:

$$X_{t,j} = (K_{t,j})^{\kappa} (Z_t L_{t,j})^{1-\kappa},$$

where κ is the capital share, and measured total factor productivity is

$$Z_{i,t} = A_t N_{j,t}^{\eta} N_t^{1-\eta} \tag{B.6}$$

where A_t represents a stationary transitory aggregate productivity shock. $N_t = \int_0^1 N_i di$ is the aggregate stock of R&D and $(1-\eta)$ captures the degree of technological spillovers. Note there are spillover effects for firm level investments in R&D to aggregate technology and these spillover effects are common in endogenous growth models (e.g., see Romer (1990)).

The law of motion for physical capital $K_{j,t}$ involves Jermann (1998) adjustment costs and the parameter ζ_k is the elasticity of new capital investments relative to existing capital

$$K_{j,t+1} = (1-\delta_k)K_{j,t} + \Phi_k\left(\frac{I_{j,t}}{K_{j,t}}\right)K_{j,t} \tag{B.7}$$

$$\Phi_k\left(\frac{I_{j,t}}{K_{j,t}}\right) = \frac{\alpha_{1,k}}{1-\frac{1}{\zeta_k}}\left(\frac{I_{j,t}}{K_{j,t}}\right)^{1-\frac{1}{\zeta_k}} + \alpha_{2,k} \tag{B.8}$$

and the parameters $\alpha_{1,k}$ and $\alpha_{2,k}$ are set to ensure adjustment costs are zero in the deterministic steady state.

The law of motion for R&D, $N_{j,t}$ also involves adjustment costs where $S_{j,t}$ is R&D investment (based on the final goods)

$$N_{j,t+1} = (1-\delta_n)N_{j,t} + \Phi_n\left(\frac{S_{j,t}}{N_{j,t}}\right)N_{j,t} \tag{B.9}$$

$$\Phi_n\left(\frac{S_{j,t}}{N_{j,t}}\right) = \frac{\alpha_{1,n}}{1-\frac{1}{\zeta_n}}\left(\frac{S_{j,t}}{N_{j,t}}\right)^{1-\frac{1}{\zeta_n}} + \alpha_{2,n} \tag{B.10}$$

There is a representative final goods producers which aggregates intermediate goods into the final good using a constant elasticity of substitution (CES) technology. The aggregator can be expressed as:

$$Y_t = \left[\int_0^1 X_{t,j}^{(\theta-1)/\theta} dj\right]^{\theta/(\theta-1)},$$

where θ is the elasticity across intermediate goods.

Given the profit maximization problem of the final goods producer, we can derive the demand function for intermediate goods produced by firm j, which is standard for New-Keynesian models.

$$X_{t,j} = \left[\frac{P_{t,j}}{P_t}\right]^{-\theta} Y_t,$$

where P_t is the nominal price of the final goods and $P_{t,j}$ is the nominal price of the intermediate goods j. The inverse demand schedule is

$$P_{t,j} = P_t Y_t^{1/\theta} X_{t,j}^{-1/\theta} \tag{B.11}$$

Substituting the production technology into the inverse demand function yields the following expression for the nominal price for intermediate good j

$$P_{t,j} = P_t Y_t^{\frac{1}{\theta}}\left[(K_{t,j})^{\kappa}(A_t N_{t,j}^{\eta} N_t^{1-\eta} L_{t,j})^{1-\kappa}\right]^{-\frac{1}{\theta}} \tag{B.12}$$

Thus nominal revenues for firm j are as follows

$$P_{t,j}X_{t,j} = P_t Y_t^{\frac{1}{\theta}} \left[(K_{t,j})^{\kappa} (A_t N_{t,j}^{\eta} N_t^{1-\eta} L_{t,j})^{1-\kappa} \right]^{1-\frac{1}{\theta}} \tag{B.13}$$

Given these definitions, firm j takes the pricing kernel M_{t+1} and the aggregate states $[P_t, K_t, N_t, Y_t, A_t]$ as given and solves the following problem to maximize the present discounted value of future real dividends as follows

$$V_{j,t}(P_{t-1,j}, K_{t,j}, N_{t,j}, P_t, K_t, N_t, Y_t, A_t) = \max_{P_{t,j}, I_{t,j}, S_{t,j}, K_{t+1,j}, N_{t+1,j}, L_{t,j}} \frac{D_{t,j}}{P_t} + E_t[M_{t+1} V_{j,t+1}] \tag{B.14}$$

subject to laws of motion for $K_{t,j}$, $N_{t,j}$, the definition of the nominal price for intermediate good j, and where real dividends for firm j are defined as follows

$$\frac{D_{t,j}}{P_t} = Y_t^{\frac{1}{\theta}} \left[(K_{t,j})^{\kappa} (A_t N_{t,j}^{\eta} N_t^{1-\eta} L_{t,j})^{1-\kappa} \right]^{1-\frac{1}{\theta}} - \frac{W_{t,j}}{P_t} L_{t,j} - I_{t,j} - S_{t,j} - \frac{\phi_R}{2} \left(\frac{P_{t,j}}{\Pi_{ss} P_{t-1,j}} - 1 \right)^2 Y_t \tag{B.15}$$

where $\Pi_{ss} \geq 1$ is the gross steady-state inflation rate and ϕ_R is the magnitude of the Rotemberg (1982) price adjustment costs.

Since firms can change their price each period and all firms face the same problem, a symmetric equilibrium exists where all firms choose the same price and same quantity. This leads to the following firm first order conditions

$$\Lambda_t = \phi_R \left(\frac{\Pi_t}{\Pi_{ss}} - 1 \right) \frac{Y_t \Pi_t}{\Pi_{ss}} - E_t \left[M_{t+1} \phi_r \left(\frac{\Pi_{t+1}}{\Pi_{ss}} - 1 \right) \frac{Y_{t+1} \Pi_{t+1}}{\Pi_{ss}} \right] \tag{B.16}$$

$$Q_t^k = \left[\alpha_{1,k} \left(\frac{I_t}{K_t} \right)^{-\frac{1}{\zeta_k}} \right]^{-1} \tag{B.17}$$

$$Q_t^n = \left[\alpha_{1,n} \left(\frac{S_t}{N_t} \right)^{-\frac{1}{\zeta_n}} \right]^{-1} \tag{B.18}$$

$$\begin{aligned} Q_t^k =& E_t \left[M_{t+1} \left(\frac{\kappa(1-\frac{1}{\theta}) Y_{t+1}}{K_{t+1}} + \Lambda_{t+1} \frac{\kappa}{\theta} K_{t+1}^{-1} \right) \right] + \\ & E_t \left[M_{t+1} Q_{t+1}^k \left(1 - \delta_k - \frac{I_{t+1}}{K_{t+1}} \left[\alpha_{1,k} \left(\frac{I_{t+1}}{K_{t+1}} \right)^{-\frac{1}{\zeta_k}} \right] + \frac{\alpha_{1,k}}{1-\frac{1}{\zeta_k}} \left(\frac{I_{t+1}}{K_{t+1}} \right)^{1-\frac{1}{\zeta_k}} + \alpha_{2,k} \right) \right] \end{aligned} \tag{B.19}$$

$$\begin{aligned} Q_t^n =& E_t \left[M_{t+1} \left(\frac{\eta(1-\kappa)(1-\frac{1}{\theta}) Y_{t+1}}{N_{t+1}} + \Lambda_{t+1} \frac{\eta(1-\kappa)}{\theta} N_{t+1}^{-1} \right) \right] + \\ & E_t \left[M_{t+1} Q_{t+1}^n \left(1 - \delta_n - \frac{S_{t+1}}{N_{t+1}} \left[\alpha_{1,n} \left(\frac{S_{t+1}}{N_{t+1}} \right)^{-\frac{1}{\zeta_n}} \right] + \frac{\alpha_{1,n}}{1-\frac{1}{\zeta_n}} \left(\frac{S_{t+1}}{N_{t+1}} \right)^{1-\frac{1}{\zeta_n}} + \alpha_{2,n} \right) \right] \end{aligned} \tag{B.20}$$

$$\frac{W_t}{P_t} = \frac{(1-\kappa)(1-\frac{1}{\theta}) Y_t}{L_t} + \Lambda_t \left(\frac{1-\kappa}{\theta} \right) L_t^{-1} \tag{B.21}$$

where Q_t^k, Q_t^n, and Λ_t represent the shadow values of physical capital, R&D capital, and price of intermediate goods, respectively.

The aggregate resource constraint is

$$Y_t = C_t + I_t + S_t + \frac{\phi_R}{2}\left(\frac{\Pi_t}{\Pi_{ss}} - 1\right)^2 Y_t \tag{B.22}$$

Monetary policy follows a Taylor-type rule that depends on the inflation, output, and lagged interest rate deviations

$$ln\left(\frac{R_t}{R_{ss}}\right) = \rho_r ln\left(\frac{R_{t-1}}{R_{ss}}\right) + (1-\rho_r)\left(\rho_\pi ln\left(\frac{\Pi_t}{\Pi_{ss}}\right) + \rho_y ln\left(\frac{\hat{Y}_t}{\hat{Y}_{ss}}\right)\right) + \sigma_\xi \xi_t \tag{B.23}$$

where $\hat{Y}_t = \frac{Y_t}{N_t}$ is detrended output, R_t is the gross nominal short rate, and ξ_t $N(0,1)$ is the monetary policy shock.

In terms of exogenous shocks, there are three more besides the monetary policy shock. Specifically, there is a transitory shock to the level of productivity along with an associated volatility shock, and we also include a shock to the time endowment, to be consistent with the time savings observed with WFH policies during the pandemic.

$$log(A_t) = (1-\rho)log(A_{ss}) + \rho log(A_{t-1}) + \sigma_{t-1}\epsilon_t \tag{B.24}$$

$$\sigma_t^2 = \bar{\sigma}^2 + \lambda(\sigma_{t-1}^2 - \bar{\sigma}^2) + \sigma_e e_t \tag{B.25}$$

$$\bar{L}_t = \bar{L} + \nu_t^L \tag{B.26}$$

$$\nu_t^L = \rho_\nu \nu_{t-1}^L + \sigma^L \epsilon_t^L \tag{B.27}$$

B.3 Parameterization

The parameterization is similar to that in Kung (2015). The only difference is the magnitude of the price adjustment costs. The price adjustment costs are set in such a way to ensure a relatively flatter Philips curve (consistent with recent data on the relationship between inflation and the output gap) and to ensure that output falls in response to the uncertainty shock. We also allow for a shock to the time endowment to simulate one of the potential effects of WFH policies. A description of each parameter along with an explanation is provided in table B.1.

Table B.1: **Parameterization for New Keynesian Endogenous Growth Model**

Parameter	Description/Explanation	Value
A. Preferences		
β	Subjective Discount Factor	0.997
	- Consistent with level of real risk-free short rate.	
ψ	Inverse Elasticity of Intertemporal Substitution	0.5
γ	Risk Aversion	10
	- GMM estimates of Bansal, Kiku, and Yaron (2007).	
B. Productivity		
ρ	Persistent of $\log(A_t)$	0.983
	- Match first autocorrelation of expected productivity growth.	
$\bar{\sigma}$	Vol. of productivity shock	1.20%
	- Match unconditional vol of measured productivity growth.	
λ	Persistence of squared vol. process	0.997
	- Match first autocorrelation of realized consumption vol.	
σ_e	Vol. of vol. shock	0.008%
	- Match std. dev. of realized consumption vol.	
C. Firm Parameters		
θ	Price elasticity of intermediate goods	6
κ	Capital share	0.33
δ_k	Depreciation rate of physical capital	0.02
	- Standard values in macroeconomics literature	
ϕ_R	Price adjustment costs	230
	- Consistent w/ flatter NKPC. Ensures output declines w/unc.	
ζ_k	Physical capital adjustment cost	4.8
	- Match rel. vol of inv. growth to cons. growth	
D. Endogenous Growth		
η	Degree of technological appropriability	0.1
	- Match steady state vlaue of R&D investment rate	
δ_n	Depreciation Rate of R&D Stock	0.0375
	- Value used by BLS for R&D stock	
ζ_n	R&D capital adjustment cost	3.3
	- Match relative vol of R&D invest. growth to cons. growth	
E. Monetary Policy		
ρ_r	Inertia coefficient	0.7
ρ_π	Inflation coefficient	1.5
ρ_y	Output coefficient	0.1
σ_ξ	Vol. of monetary policy shock	0.3%
	- Standard values in macroeconomics literature	
F. Time endowment		
ρ^ν	Persistence of shock to time endowment	0.99
	- Allows near-permanent shift	
σ^L	Vol. of shock to time endowment	0.03
	- Generates shock equal to one percent of total time endowment	
τ	Weight on leisure in consumption-leisure bundle	1.57
	- Ensures one-third of time is devoted to labor.	