Testing Demand-Led Growth and Accommodating Supply*

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Abstract: Post-Keynesian research proposes macroeconomic growth is led by aggregate demand. A recent paper (Fazzari, Ferri, and Variato, Cambridge Journal of Economics, 2020, FFV hereafter) shows theoretically that productive capacity converges to accommodate demand-led growth under general conditions. This model and related post-Keynesian research pose a serious challenge to orthodox macroeconomics: demand leads supply. But empirical tests of these models are scarce. This paper helps to fill that gap by considering whether the FFV model led by demand shocks can replicate the time-series behavior of both the demand and supply sides of the US economy. First, we assess whether the FFV model can replicate the persistence, volatility, and co-movements of the levels and growth rates of seven key macroeconomic variables at business-cycle and lower frequencies. Second, we assess whether the model can replicate the impulse-response functions of these macroeconomic variables following a shock to the level of autonomous demand. We find that the model performs qualitatively and quantitatively as well or better than a benchmark Real Business Cycle model with labor market frictions along these dimensions.

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1 Introduction

What is the role of demand in driving macroeconomic activity? No one would deny demand is necessary to motivate production in a market economy; what is not sold will not be produced. However, mainstream macroeconomic models since (at least) Modigliani (1944) have relegated the role of demand to the short run, asserting that endogenous market-driven adjustments of wages and prices assure sufficient demand to purchase full-employment, potential output. These adjustments may not be instantaneous, and therefore autonomous fluctuations in aggregate demand may affect real variables for some time, but the long-run path of an economy is typically understood as independent of direct effects of spending choices, driven instead entirely by the supply side.

This perspective changed to some extent in the last two decades of the 20th century. In "new consensus" models, wise monetary policy replaced nominal adjustment as the instrument to restore aggregate demand to potential levels. This change elevated the importance of activist policy relative to "natural" market forces in generating convergence of output to a supply-driven path. But it still relegated to the role of autonomous demand dynamics to the short run, a period now defined by the speed of the transmission of monetary policy to spending decisions.

The events following the Great Recession have challenged this mainstream consensus, forcing macroeconomists to rethink the role of aggregate demand in shaping the medium- to long-run performance of an economy. In the US, output failed to regain its pre-recession trend at any point in the approximately 12 years from the beginning of the Great Recession to the COVID-19 pandemic lockdown. Some analysts, interpreting this disappointing outcome through the conventional new consensus lens, looked for some kind of a supply shock, independent of the demand collapse that caused the Great Recession (Fernald, 2015; Cette, Fernald, and Mojon, 2016). But another interpretation emerged raising the suspicion that weak demand can constrain the economy beyond the short run. Summers (2014), harking back to Alvin Hansen, labeled this phenomenon "secular stagnation."

In this paper, we present a simple framework to empirically study the role autonomous aggregate demand—components of demand independent of economic conditions—plays in shaping medium- to long-term economic performance. Our model is based on the demand-led growth model from Fazzari, Ferri and Variato (2020, hereafter FFV) with a supply side that, in almost all cases, accommodates the demand-led path. Supply in this model accommodates demand growth (not just demand levels) through hysteresis effects of demand on labor supply growth and labor productivity. Our model is, in one sense, extreme: the proximate determinant of output and employment at any horizon is demand. Quantities bear all the burden of adjusting supply and demand; our model omits relative prices and nominal variables. We then estimate this simple Keynesian growth model and assess its empirical performance along three dimensions. First, we ask whether it can match the volatility, persistence and co-movements of seven macroeconomic variables at both business-cycle and lower frequencies. Second, we compare the estimated model impulse-response functions induced by a large demand shock to empirical impulse responses presented in a recent study by Girardi, Paternesi and Stirati (2020) of large exogenous autonomous demand shocks. Third, we present an empirical test of the key hysteresis parameters in the model to explore whether the model's result that demand leads supply is empirically plausible.

While there is an extensive literature on demand-led growth models - indeed, this is one of the pillars of Post-Keynesian Economics (Lavoie, 2014) - there is surprisingly little empirical work estimating the structural parameters of a demand-led, dynamic macroeconomic model and comparing its predictions to the data. Recent studies have tested some implications of Post-Keynesian demand-led growth models (Girardi and Pariboni, 2020; Haluska, Braga and Summa, 2020; Girardi et. al, 2020). To the best of our knowledge, however, we are the first to use this kind of model to study quantitatively business-cycles and growth in a unified framework and to be explicit about the stochastic components driving the data.

Recent mainstream research analyzing persistent effects of aggregate demand slumps on economic performance usually resorts to the zero-lower bound for short-term interest rates as the crucial reason for demand effects beyond the short run (Benigno and Gornaro, 2018; Eggertsson, Mehrotra and Robbins, 2019). We contend, however, that monetary policy may not be effective at restoring full employment and potential output even when short-term nominal interest rates are not pinned at zero.

Our main results are as follows: First, we find that calibrating the model using simple OLS regressions yields second moments that match the stylized facts of the business cycle well. In particular, we match the correlations between employment, unemployment and labor productivity better than traditional Real Business Cycle models augmented with search and matching frictions. Second, we find our model reproduces, at least qualitatively, most of the responses to a plausibly exogenous autonomous demand shock over a decade-long horizon, as estimated by Girardi, et al. (2020).

The rest of the paper is organized as follows: Section 2 presents our baseline framework.

Section 3 presents the data used, along with our definition of autonomous demand and our calibrated values. Section 4 presents our results in terms of second moments and Impulse Response Functions. Section 5 concludes.

2 A demand-led growth model

The model we use to motivate our empirical work is presented in detail by FFV (2020) and will be summarized here. Aggregate demand (Y_t^D) determines output (Y_t) as long as demand is less than aggregate supply (Y_t^S). The demand side is similar to models widely used in the supermultiplier literature (Serrano, 1995). Demand is composed of three components: consumption and business investment, both induced by the state of the economy, and autonomous demand that evolves through time independent of the state of the economy.

Since autonomous demand plays a key role in both driving the theoretical results and in our quantitative application, it's worth explaining in more detail what this concept entails. The key idea is that there is a component of aggregate spending that is independent of income or the actual state of the economy. An intuitive example is government spending devoted to military spending: to the extent that military expenditures are driven by political considerations, we would expect them to be independent of the state of the economy. In our quantitative exercise we discuss several possible candidates at length. With this in mind, we proceed to summarize the model.

Induced consumption depends on expected income:

$$C_t = (1-s)(1+Eg_t)Y_{t-1} \tag{1}$$

where Eg_t is the expected growth rate of income based on information available through period $t-1$ and s is the constant marginal propensity to save.[1] Expected growth rates adjust adaptively with speed of adjustment α:

$$Eg_t = (1-\alpha)g_{t-1} + \alpha Eg_{t-1} \tag{2}$$

Business investment in period t (I_t) becomes productive capital in period $t+1$ (K_{t+1}):

$$I_t = K_{t+1} - (1-\delta)K_t = \hat{v}_t(1+Eg_t)^2 Y_{t-1} - (1-\delta)K_t \tag{3}$$

[1] In the model of FFV (2020) taxes are not modelled explicitly. A proportional income tax rate can be included in s without loss of generality.

where δ is a geometric depreciation rate. The target capital output ratio ($\hat{v}_t$) that drives investment evolves according to a partial adjustment rule to eventually reach the long-run, technologically determined capital-output ratio (v^*)[2]

$$\hat{v}_t = (1-\lambda)v_{t-1} + \lambda v^*. \tag{4}$$

The parameter λ controls the speed of adjustment as in Freitas and Serrano (2017). Autonomous demand (F_t) grows at an exogenous growth rate g_t^*:

$$F_{t+1} = F_t(1+g_t^*). \tag{5}$$

Note that this specification allows autonomous demand growth to change over time, but those changes are independent of the state of the economy.
Aggregate demand is the sum of the demand components and output equals demand (unless demand exceeds the supply-determined potential to produce):

$$Y_t = Y_t^D = C_t + I_t + F_t \tag{6}$$

Substituting specifications for the demand components into this equation and dividing by lagged output yields the law of motion for output growth:

$$1 + g_t = (1-s)(1+Eg_t) + \hat{v}_t(1+Eg_t)^2 - v_t(1-\delta)(1+g_t) + f_t(1+g_t) \tag{7}$$

where $g_t = Y_t/(Y_{t-1}-1,)$, $v_t = K_t/Y_t$, $f_t = F_t/Y_t$. If autonomous demand grows at a constant rate $g_t^* = g^*$, the model has a steady state given by:

$$g_t = Eg_t = g^* \tag{8}$$

$$v_t = \hat{v}_t = v^* \tag{9}$$

$$f_t = f^* = s - v^*(g^* + \delta) \tag{10}$$

Depending on parameter values, the dynamics of the model can be stable or unstable. As discussed in FFV (2020), however, empirically calibrated values for the parameters make stability likely. If this is the case, the steady state acts as a center of gravity attracting realized values of the endogenous variables, especially if the growth rate of autonomous demand

[2]Our neoclassical might think of this as a reduced-form whose foundation is some form of adjustment costs, which prevents the capital stock from realizing it's long-run level immediately.

is not highly variable.

The main innovation in FFV (2020) is to model the connection between demand-led growth and the supply side explicitly. Aggregate supply (Y_t^S) is a linear function of the available labor force (L_t)[3] :

$$Y_t^S = A_t L_t \tag{11}$$

Because capital is produced and firms will want to assure they have enough capacity to meet demand, we abstract from supply-side capital constraints and assume that labor resources alone drive aggregate supply. The unemployment rate is one minus the capacity utilization rate:

$$u_t = 1 - (Y_t^D)/(Y_t^S) \tag{12}$$

Hysteresis effects connect supply growth to demand dynamics through two structural channels. First, labor force growth (g_t^{LS}) depends on the strength of the economy as measured by the unemployment rate:

$$g_t^{LS} = \theta_0 - \theta_1 u_{t-1} \tag{13}$$

Second, the growth rate of the labor productivity term (g_t^A) depends, again, on the current state of the economy through the unemployment rate as well as the rate at which the capital stock is renewed by investment (the growth rate of the capital stock plus the depreciation rate):

$$g_t^A = \phi_0 - \phi_1 u_{t-1} + \phi_2 (g_{t-1}^K + \delta). \tag{14}$$

The second term in the productivity growth equation captures a Verdoorn effect of the growth of the economy (since g_t^K is highly correlated with output growth, equal in steady state) on the growth of productivity. FFV (2020) contains more motivation and references to justify these supply-side equations.

The key result in FFV (2020) is that supply growth will accommodate the demand growth path as long as the effect of unemployment on supply growth is positive ($\theta_1 + \phi_1 > 0$) and

[3]The underlying assumption is that there is a fixed-coefficient, Leontief production function of the form $Y_t = \min\{A_t L_t, K_t/v\}$, and that there is labor scarcity in the sense that $A_0 L_0 < K_0/v$. Given these assumption, and that as shown below, in the steady growth path $g^A + g^L = g^K = g^*$, labor remains the binding production factor, which allows us to write a production function linear in labor.

the unemployment rate in steady state:

$$u^* = \frac{\theta_0 + \phi_0 - g^*(1 - \phi_2) + \phi_2\delta}{\theta_1 + \phi_1} \tag{15}$$

remains above an exogenous minimum rate ($\hat{u}$). Thus, the economy can be driven by aggregate demand "beyond the short run" of mainstream DSGE models in which demand dynamics cease to affect real outcomes after prices fully adjust. Furthermore, stagnant demand pulls supply-side potential demand down with it. There is no "natural rate" of either unemployment or growth determined by supply-side factors, In contrast, both the unemployment rate and, especially, the growth of potential output depend on the dynamics of aggregate demand.

To evaluate the model quantitatively, we need to add stochastic components. Considering the demand-driven focus of the model, it is natural to consider a shock to autonomous demand. Let's re-write equation (5) in the following form

$$F_t = F_{t-1}(1 + g^*) = F_{t-2}(1 + g^*)^2 = ... \tag{16}$$

And by successive iterations, we obtain:

$$F_t = F_0(1 + g^*)^t \tag{17}$$

A stochastic version of the model can be obtained by adding the shock $u_t = \exp(v_t^D)$ in a multiplicative fashion. In other words:

$$F_t = F_0(1 + g^*)^t \cdot u_t \tag{18}$$

Let us apply natural logarithms:

$$\ln F_t = \ln F_0 + t \ln(1 + g^*) + \ln u_t \tag{19}$$

Without loss of generality, assume $F_0 = 1$, and the exogenous growth is empirically reasonable, hence $g^* \sim 0$. Use the definition for u_t to obtain:

$$\ln F_t = tg^* + v_t^D \tag{20}$$

To complete our description, we specify the properties of the stochastic process, v_t^D. We assume a simple $AR(1)$ process of the form:

$$v_t^D = \rho_D v_{t-1}^D + \varepsilon_t^D \tag{21}$$

Where the white noise shock is a gaussian i.i.d process:

$$\varepsilon_t^D \sim i.i.dN(0, \sigma_D^2) \tag{22}$$

These white-noise shock ε_t^D, along the propagation mechanisms inside the model, account for all the cyclical and low-frequency fluctuations in the data.

The model equations, (1) through (11), along with the stochastic shocks, (16) and (17), define a system of non-linear stochastic difference equations which must be solved to obtain the dynamics for the whole model. However, given that this is not analytically possible, we will use our calibrated parameters, initial conditions and the previous equations to extensively simulate the model, as done in FFV (2020). The innovation is that we can now exploit the stochastic nature of the model to evaluate statistically some of its qualitative and quantitative predictions.

3 Empirical Validation

3.1 Data

We use data on the components of U.S. GDP for the period 1959Q1 - 2019Q4 compiled by the Bureau of Economic Analysis and downloaded from the St. Louis Federal Reserve Bank's "FRED" data site. All data were downloaded in nominal form and then deflated by the same price index, the chain-weighted deflator for personal consumption expenditure. This index is the Federal Reserve's preferred measure of aggregate inflation. Using a common deflator is appropriate for studying demand-led dynamics because the objective is to capture expenditure flows. So-called "real" series for separate GDP components such as business fixed investment and personal consumption expenditure attempt to adjust for quality changes. For example, personal computer price indexes decline dramatically more than the actual purchase price of these machines reflecting the fact that they are faster and have more memory and storage than earlier products. These quality adjustments may reflect that new computers are somehow "better" than their earlier counterparts, but higher quality is not reflected, other things equal, in expenditure.

Our model identifies three components of demand that drive output: induced consumption, induced business investment, and autonomous demand. Business investment adds directly to productive capacity and therefore our business investment variable excludes residential construction and inventory changes. The definition of autonomous demand is central to the logic of the FFV model we study, but there are ambiguities in defining what is indeed "autonomous." We consider several measures to explore the robustness of results to this definition.

All definitions of autonomous demand include consumption and investment spending by federal, state, and local governments (Allain, 2015). In addition, all our autonomous demand definitions include government spending on social programs. In the U.S., this spending is almost entirely for health care (Medicare and Medicaid). In the national accounts, this spending is treated as a transfer to the private sector and then added, dollar-for-dollar, to personal consumption expenditure. But it is clear that this spending is not induced by cash income flows to households. These spending categories are large injections of demand by government and are just as "autonomous" as other parts of government spending that are almost always identified as autonomous in related empirical studies.

A second definition of autonomous demand adds government transfer payments to retirees and the disabled, Social Security. These payments are surely autonomous, in the sense that they are steady, defined-benefit expenditures that do not depend on the state of the economy. Ambiguity arises, however, because Social Security income is not necessarily spent and therefore does not add dollar-for-dollar to demand like government health care spending. However, Social Security is large and much of it goes to households of limited means. Most of this spending likely supports demand and that demand is largely autonomous.

The third definition of autonomous demand adds exports (Nah and Lavoie, 2017). For almost any country, exports are likely independent of domestic economic shocks. The U.S. is large enough, however, that its own exports could be affected by domestic shocks because those domestic shocks could spill over in non-trivial ways to its trading partners. Nonetheless, there is a good case that even US exports are largely autonomous, especially at lower data frequencies.

The fourth and final definition of autonomous demand adds residential construction. Some author's have argued that residential investment is driven fundamentally by credit flows and the accumulation of debt; hence, in recent U.S history, they have been largely detached from current output (Fiebiger, 2018; Pérez-Montiel and Pariboni, 2021). The same author's have also argued that in the long-run, the growth rate of residential investment must be determined by the rate of population growth, which they presume as exogenous. As it's well-known, however, both Malthusian and modern theories of fertility assume that population growth is dependent on the state of the economy (Barro and Becker, 1989).

Table 1: Properties of autonomous demand series

	Correlation?	Persistence	Std. Dev
$\ln Z_1$	0	0.987	0.012
$\ln Z_2$	0	0.990	0.011
$\ln Z_3$	0	0.936	0.019

Table 1 shows the properties of these three autonomous demand series, after applying logarithms and linearly detrending them. A measure of autonomous demand based only on fiscal expenditures shows very similar persistence and volatility properties than a broader measure incorporating fiscal transfers, exports and residential investment. However, the key difference between them is the correlation that they show with output: Since fiscal policy is countercyclical, a measure based only on government expenditure shows negative correlation with the cyclical component of output; while a broader measure predicts positive correlation. The third measure of autonomous demand, which adds net inflows of consumer credit, is slightly less persistent, but is almost twice as volatile as the other two measures. Our preferred measure is $\ln Z_2$, given our previous discussion of the shortcomings of residential investment; we will exploit the properties of this stochastic process in the calibration below; however, we can check the robustness of the empirical results to altering the volatility and persistence of the shock.

With regards to the supply side, we use time series on the unemployment rate and employment, measured as total workers, from FED-QR. Finally, labor productivity is computed as output divided by employment.

3.2 Methodology and calibration

How can we test a fully-specified, dynamic, general equilibrium demand-led growth model such as the one outlined above? In the context of super multiplier growth models, empirical tests of the model are rather scarce. Girardi and Pariboni (2016) test the balanced-growth implications of the model; in particular, the model predicts that the growth rate of output, consumption and capital all converge to the growth rate of autonomous demand. This implies that both variables exhibit a common stochastic trend; hence, autonomous demand and output are co-integrated in the model. They show that this co-integration prediction holds for their measure of autonomous demand and output in U.S data. Girardi, Paternesi and Stirati (2020) construct series of autonomous demand for 34 OECD countries for the period 1960-2015 and estimate the impulse-response functions of output and other key macroeconomic variables to autonomous demand shocks. They show that output, the capital stock, labor-force participation and several other macroeconomic variables expand persistently after an autonomous demand shock.

While the previous empirical literature has provided solid support for some key predictions of the super multiplier approach to growth and distribution, their empirical methods are agnostic with regards to the structural parameters of the model, whose values are necessary to provide a range of interesting quantitative policy exercises, such as what would happen if the growth rate of autonomous expenditure was increased by a percentage point, presumably by the fiscal authorities. The values of these parameters were obtained by simple univariate regressions in Fazzari et. al (2020). To asses whether the values of these calibrated parameters are empirically consistent with the data, we conduct two empirical exercises: First, we ask whether these parameter values can reproduce the key summary statistic that characterize business cycle fluctuations in the US economies for seven major macroeconomic variables. These statistics are the correlations across these variables, their relative and absolute volatilities, and their persistence. Second, we ask whether these parameter values can reproduce the impulse-response functions estimated by Girardi et. al (2020).

In many ways, this 'ultra-Keynesian' exercise of asking whether a simple supermultiplier model augmented with a stationary but persistent autonomous demand shock can completely characterize business cycle fluctuations is bold, and a very stringent empirical test. Nevertheless, by assessing the discrepancies between the model and the data we can help to build intuition by understanding along which dimensions the model fails and succeeds, and therefore to extend or modify the model appropriately. It also shows how much of the data a demand-led growth model can go without making references to technology shocks, a core element of DSGE models in either their Real-Business Cycle or New-Keynesian incarnations.

Concretely, our methodology proceeds as follows. We first use the calibrated values shown in Table 2, along with the stochastic process for the demand shock, to generate S simulations of length T for our time-series of interest. For each simulation, we compute the second moments of interest. We save these values, and then use the empirical distribution of these moments across the S simulations to build 95% confidence intervals for our statistics of interest. We then asses whether the statistics found in actual data are inside these confidence intervals as a formal measure of model fit; this can be interpreted as an exact statistical test based on a Monte Carlo procedure (Gregory and Smith, 1991); or, as mentioned before, an informal guide for model reformulation.

Table 2: Calibrated parameter values

Parameter	Value
g^*	0.0063
v^*	4.8000
$(1-s)$	0.6600
λ	0.0225
α	0.9750
δ	0.0250
θ_1	0.0500
ϕ_1	0.0125
ϕ_2	0.5000
ρ_Z	0.9897
σ_Z	0.0105

Table 2 displays the calibrated values of our parameters. Most of these parameter values are taken from Appendix 1 of FFV; divided or multiplied by 4 in order to adjust for the fact that we use quarterly data. For example, θ_1, which measures the effect of the unemployment rate on labor supply growth, is obtained as 0.20 by fitting a variety of OLS regression. We divide this value by 4 and obtain 0.05, which we use as a benchmark.

The exceptions to this rule are the marginal propensity to save, the capital-output ratio, and the parameter values for the $AR(1)$ process that governs the shocks to autonomous demand. The first two parameters are selected to match the shares of consumption and investment in GDP in the data. The values for the autonomous demand shock are taken from Table 2, we de-trend linearly our time series for autonomous demand, and fit a simple AR(1) process to the residual.

To calculate impulse response functions, we proceed as follows. We initialize the model at the steady state, and compute a path of the endogenous variables in absence of shocks. We then initialize the model again at the steady state, and we shock the the first period, i.e,

$\varepsilon_1^D = \delta$ and $\varepsilon_t^D = 0 \quad \forall t > 1$, and compute the path of the endogenous variables. We then subtract both vectors; $E[Y_{t+h}|\varepsilon_1^D = \delta] - E[Y_{t+h}|\varepsilon_1^D = 0] = IRF_h$. The size of the shock is δ; which is typically specified to be 1. However, since we are interested in replicating the results from Girardi, Paternesi and Stirati (2020), we set the size of this shock to be a 5% increase in the steady-state value of F, which is the criteria used by the authors.

4 Results

4.1 Second moments

As mentioned before, we are interested in exploring whether the model can quantitatively match the the co-movements, persistence and volatility of seven key macroeconomic variables for the US. We first examine the fit of the model when using only business-cycle fluctuations. We use the Baxter-King (1999) filter to the natural logs of the data in order to extract frequencies between 6 and 32 quarters, which are commonly though to contain business-cycle fluctuations, we use the same procedure to the data generated by the model, and report the results of this exercise in Table 3.

Table 3: Business Cycle moments in the model and the data

	Correlations		Persistence		Rel. Volatility	
Variable	Data	Model C.I	Data	Model C.I	Data	Model C.I
$\ln Y$	1.00	-	0.93	[0.92, 0.96]	1.00	-
$\ln C$	0.93	[0.93, 0.96]	0.95	[0.92, 0.95]	1.08	[1.01, 1.03]
$\ln I$	0.74	[0.98, 0.99]	0.94	[0.91, 0.95]	3.04	[1.16, 1.23]
$\ln F$	0.57	[0.75, 0.86]	0.90	[0.87, 0.92]	0.84	[1.14, 1.34]
u	-0.83	[-0.81, -0.69]	0.94	[0.90, 0.94]	0.50	[0.77, 0.89]
$\ln L$	0.77	[0.84, 0.90]	0.94	[0.90, 0.94]	0.54	[0.83, 0.94]
$\ln A$	0.68	[0.37, 0.56]	0.91	[0.95, 0.98]	0.65	[0.44, 0.55]

Note: All model confidence intervals are computed at the 95% level.

Table3 shows that many of the stylised facts familiar to macroeconomists are insensitive to our data transformations, explained in the previous section. All components of aggregate demand show a very high correlation with output; unemployment is countercyclical, while employment, and hence, labor productivity, is procyclical. All series are fairly persistent. Finally, the relative volatility of investment is roughly 3 times that of output; consumption shows a similar volatility to output, and unemployment, employment and labor productivity are substantially less volatility than output.

In many ways, the critical test for our model is whether it can match the co-movements of the unemployment rate. Since the unemployment rate, instead of relative prices, bears the burden of adjusting aggregate supply and demand, assessing whether the model produces reasonable behaviour of the unemployment rate is crucial. In this regards, the model seems to match the behaviour of unemployment very well: it produces very strong counter-cyclical unemployment, with behaviour very close to the data; a very good fit in terms of persistence, and a slightly more volatile unemployment rate that the one found in the data.

The model also produces reasonable behaviour along other dimensions: it matches the persistence of most macroeconomic variables; and matches qualitatively and quantitatively all the correlations between output and other variables, with the exception of labor productivity, which has a correlation with output slightly lower than the one in the data. Our model is able to reproduce pro cyclical productivity due to two features: first, increases in input usage do not bring about static diminishing returns, since our production function has fixed coefficients; second, when the economy is hit with a demand shock, the transitory decrease in unemployment sets in motion an increase in the growth rate of labor productivity in the supply-side of the model.

Finally, we can ask whether the model matches the relative volatility of the series. In this regards, while the match is reasonable, there is a lot of room for improvement: the model-implied volatility of investment is 1/3 of the one present in the data; likewise, it overshoots the volatility of autonomous demand, unemployment, and employment. It also undershoots slightly the behaviour of labor productivity.

We next ask whether the model can replicate a broader set of correlations across variables; in particular, we are interested in analysing the behaviour of the supply side of the model with more detail. Table 4 reports the correlation matrix for our seven variables: in the lower diagonal, we present the correlations present in the data; in the upper diagonal, we present the confidence intervals of the model-implied correlations.

Can this simple Keynesian growth model outperform a benchmark Real Business Cycle model, augmented with Labor Market Frictions, say, as in Andolfatto (1996), at least in some dimension? The previous table suggests it can. In particular, we focus on two key moments: The correlation between employment and labor productivity, and between unem-

Table 4: Correlation Matrix in the model and the data

	lnY	lnC	lnI	lnF	u	lnL	lnA
lnY	-	[0.93, 0.96]	[0.98, 0.99]	[0.75, 0.86]	[-0.81, -0.69]	[0.84, 0.90]	[0.37, 0.56]
lnC	0.93	-	[0.98, 0.99]	[0.44, 0.62]	[-0.60, -0.50]	[0.67, 0.72]	[0.61,0.72]
lnI	0.74	0.70	-	[0.60, 0.72]	[-0.72,-0.60]	[0.76,0.82]	[0.50,0.65]
lnF	0.57	0.45	0.31	-	[-0.94,-0.86]	[0.88,0.94]	[-0.20,0.10]
U	-0.83	-0.81	-0.85	-0.49	-	[-0.99,-0.97]	[0.17,0.26]
lnL	0.77	0.77	0.85	0.44	-0.95	-	[-0.09,0.03]
lnA	0.74	0.64	0.25	0.42	-0.28	0.14	-

Obs: Lower triangle: Data. Upper Triangle: Model C.I

ployment and labor productivity. As it's well know, the correlation between employment and labor productivity is 1 for most benchmark RBC models (Christiano and Eichanbaum, 1992), while in the data, as shown in Table 4, this correlation is 0.14, very close to 0. In our model, the correlation between employment and labor productivity is practically 0, which is substantially closer to the data. In an RBC model, this correlation occurs because a shock to total factor productivity immediately shifts the labor demand curve to the right; in our model, a demand shock increases instantly employment, and decreases unemployment, but labor productivity growth reacts the next period, after the cumulative impact of learning by doing has taken place.

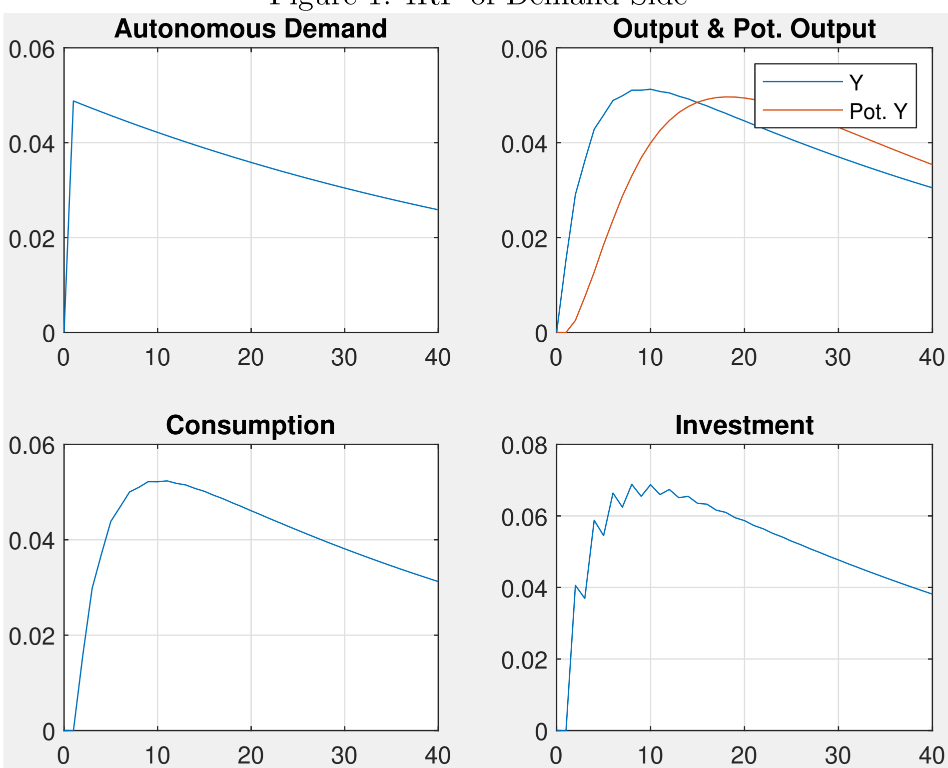
Addittionally, our model predicts a correlation between labor productivity and unemployment that is slighlty positive, while a benchmark search and matching model has the counterfactual prediction that the correlation between unemployment and productivity is essentially -1 (Shimer, 2005). In the data, the correlation between labor productivity and employment is faintly countercyclical, which puts arguably less distance between our model and the data than a search and matching model of the labor market.

It should be noted that we are not claiming our model is empirically superior than current, medium scale DSGE models, as for example embedded in Smets and Wouters (2007) or Christiano, Eichenbaum and Evans (2005). We are claiming that a simple version of Keynesian growth theory is able to deliver empirical predictions which are as reasonable as the simple, core models of the current DSGE approach. Hence, we think a Keynesian approach has some notable empirical merits and is worth further study by a broader part of the profession.

4.2 Impulse Response functions

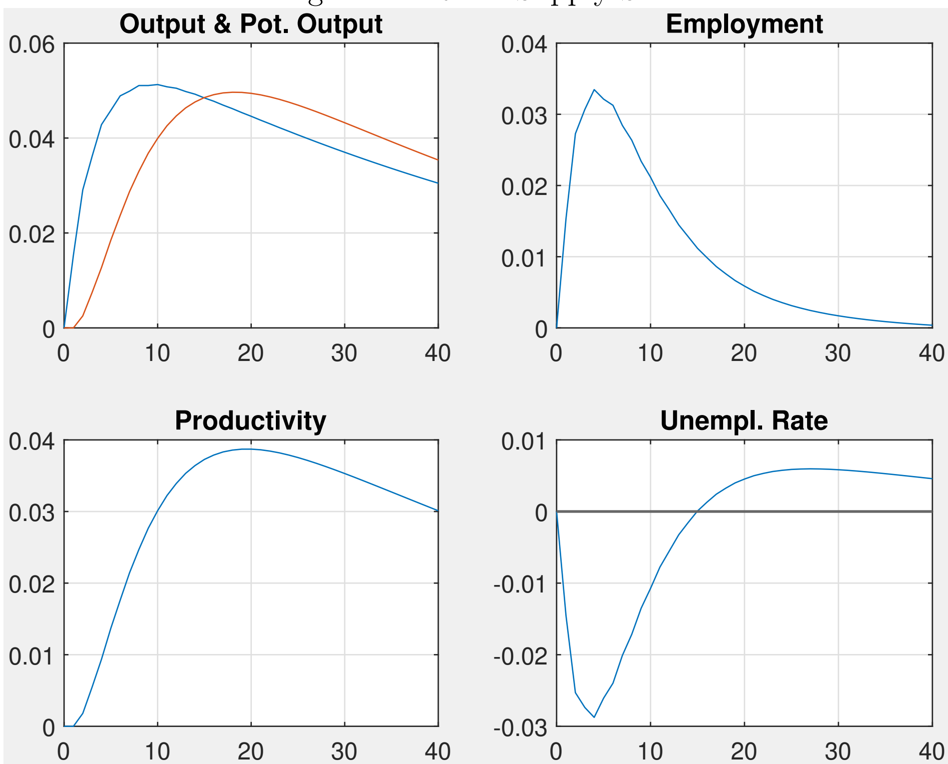
In this section, we study whether the Impulse Response Functions produced by the model can match the IRF estimated by local projectiosn by Girardi et. al (2020). We take this as independent empirical validation of the model: given that we have picked the parameters of the model to match explicitly the moments found in the data, claiming that the model produces a good fit is perhaps not particularly interesting. However, if we use those same parameter to examine how well the model can match the response of several macroeconomic variables to an autonomous demand shock, this can serve as an independent, informal measure of goodness of fit. Figures 1 and 2 reproduce the response of demand and the supply side of the economy, respectively, to an autonomous demand shock.

Figure 1: IRF of Demand Side



We first examine the fit of of the demand side in response to a shock. Three feature of these IRF are worth mentioning: First, they all produced hump-shaped responses of output, consumption and investment to an autonomous demand shock. This is encouraging, since this pattern is the one found by Girardi et. al (2020). Second, after ten years of the shock, the response of output to the shock if roughly 3.1% of it's initial level, which is exactly the same magnitude as the one found in the aforementioned paper. Finally, we can compute the average elasticity of output to a demand shock, which is 1.1 in our model, moderately above the 0.7 found by our colleagues.

Figure 2: IRF of Supply Side



The response of the supply side is also encouraging. Employment spikes rapidly after 5 quarters, and then monotonically decreases until almost reaching 0 after 40 periods. Productivity builds up slowly, reaches a peak after 5 years, and then monotonically decreases. Finally, the unemployment rate decreases rapidly after the demand shock, and then overshoots it's equilibrium value after 15 quarters. It then decreases monotonically slowly to it's steady-state value.

5 Conclusion

This paper presents a simple Post-Keynesian growth model where the growth rate of autonomous aggregate demand determines the growth rate of output and the steady-state level of unemployment, and it asks whether it can reproduce the most salient features of the U.S business cycles, as measured by the second moments of seven key macroeconomic variables, and the response of the economy to substantial autonomous demand shock. We find that the model performs at least as well as a real business cycle model with search and matching frictions along these dimensions, and hence, there is no immediate empirical reason to dismiss the model as a promising candidate to explain growth and business cycles in mature capitalists economies. We hope this stimulates further refinement and extensions of this Keynesian growth framework.

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