Technology Adoption in Input-Output Networks

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Abstract

This paper investigates the role of network structure on technology adoption. In particular, we study how the network of individual agents can slow down the speed of adoption. We study this in the context of the Python programming language by modeling the decisions to adopt Python version 3 by software packages.[1] Python 3 provides advanced features but is *not* backward compatible with Python 2, which implies adoption cost. Moreover, packages form an input-output network through dependency on other packages in order to avoid writing duplicate code, and they face additional adoption cost from dependencies without Python 3 support. We build a dynamic model of technology adoption that incorporates the input-output network. With a complete dataset of package characteristics for historical releases and user downloads, we draw a complete input-output network and develop a new estimation method based on the dependency relationship. Estimation results show that the average cost of one incompatible dependency is one-third the cost of updating a package's code. Simulations show that the input-output network contributes to 1.5 years of adoption inertia. We conduct counterfactual policies of promotion in subcommunities and find significant heterogeneous effects on the adoption rates due to differences in network structure.

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[1]Packages are also known as libraries, (sub)routines, or modules in other programming languages.

1 Introduction

> *If one examines the history of the diffusion of many inventions, one cannot help being struck by two characteristics of the diffusion process: its apparent overall slowness on the one hand and the wide variations in the rates of acceptance of different inventions on the other.*
>
> – Rosenberg (1972)

Technological innovation has been one of the most important sources of productivity and economic growth (DeLong (2002), Mansfield, Mettler, and Packard (1980)), yet slow technology adoption is still a common phenomenon in many sectors (Geroski (2000)). The rich literature of technology adoption has shown many factors that can slow down the speed of adoption: e.g., organization (Atkin et al. (2017)), competition (Gowrisankaran and Stavins (2004)), network effects (Saloner and Shepard (1995)), etc.[2] This paper contributes to the literature by examining another important channel through which technology adoption can be affected – namely, input-output networks.

As the economy becomes more disaggregated, firms specialize in one specific type of product or service and form input-output networks.[3] Specialization generates efficiency gains but the linkages between firms might have adverse effects on new technology adoption (Katz and Shapiro (1985)). For example, wireless carriers are unable to adopt 5G technology without the 5G equipments from suppliers. If suppliers experience negative shocks or are pessimistic about the new technology, 5G adoption for the whole society might stall.[4]

The extent to which an input-output network can affect technology adoption depends importantly on the network structure. Consider two different network structures illustrated in Figure 1: Agent 3 in case (b) is much more influential on the new technology adoption rate of the whole industry than case (a). Policies that aim to promote a faster adoption rate needs to take into consideration the network of individual agents.

This paper investigates how network structure affects individual technology adoption

[2]For more examples, please refer to the excellent survey by Atkin et al. (2017), Hall and Khan (2003), and Hall (2009)

[3]It is also known in other literature as vertical or input-output networks.

[4]Other examples of technology adoption in input-output networks include payment systems, industry 4.0, etc.

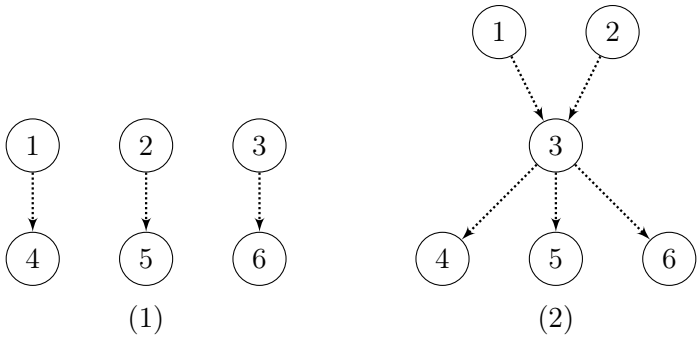


Figure 1: Examples of Input-Output Networks

decisions. We study this in the context of the Python programming language, in particular, the transition from Python version 2 to version 3.[5] Python is one of the most popular programming languages in the world. Python 3 was a major release in 2008 that experienced slow adoption.[6] Python 3 provides several fundamental improvements but is *incompatible* with Python 2.[7] In other words, code written for Python 2 often fail to work on Python 3, and vice versa.

Like other programming languages, most functionalities on Python are provided by third-party packages. These packages form an input-output network through dependency requirements: downstream packages are built using functionalities provided by upstream packages, or upstream packages are dependencies for downstream packages. In order to use a package, the end user has to install both the package itself as well as all its upstream dependencies.

The incompatibility between Python 2 and 3 implies adoption costs for package developers. In order to use new features of Python 3, packages have to update their source code. If one or more of their upstream dependencies have yet to adopt Python 3, additional adoption cost is incurred.[8] Our research focuses on adoption decisions of third-party packages.

We consider each package an individual agent making the adoption decision, and model utility as a function of user downloads (Fershtman and Gandal (2011)). For any of the most commonly-known motivations behind contributions to Open Source Software (OSS) (such

[5]Similar issues exist in other software or programming languages, such as Windows DLLs, Fortran, and Ruby. We study Python mainly due to data availability.

[6]The Python 3 adoption process has been widely considered a slower-than-optimal process.

[7]Appendix A provides a list of new functionalities in Python 3 that are incompatible with Python 2.

[8]Typical solutions (or costs) include looking for alternative dependencies with Python 3 support, or update the necessary components of the dependency to support Python 3.

as altruism, career incentives, ego gratification, etc.), more user downloads are always better for the package developers.

To understand how the dynamics of technology adoption are affected by network structure, we build a dynamic model in which each package makes an irreversible decision to adopt Python 3, following Rust (1987) and Keane and Wolpin (1997). This adoption decision implies changing the package to be compatible with Python 3. Our model highlights an intertemporal trade-off: if packages adopt early, they receive more user downloads but incur higher adoption costs; if packages adopt later they might have lower adoption cost due to future adoption decisions of upstream dependencies. The solution of the optimal stopping problem requires a prediction of future states for a package itself and for each of its dependencies, as well as those of the dependencies of dependencies, and so on.

With a complete dataset of package characteristics, historical releases and user download statistics,[9] we estimate our model by taking advantage of a unique characteristic of this dependency network, namely, directed network. The rich dataset allows us to draw a complete input-output structure of all packages. We group packages into various layers based on the dependency relationship, and calculate the adoption probability layer by layer.

Our model allows for rich heterogeneous adoption costs across agents (Gowrisankaran and Stavins (2004), Ryan and Tucker (2011)). We measure the detailed heterogeneous effects by incorporating all the actual links between packages and different package characteristics.

The variation in certain dependency characteristics affects utility in the future but not in the current period. We use that variation to identify the discount factor, which is typically not separately identified in many dynamic discrete choice settings.

Results from the structural estimation show that packages benefit from more user downloads. We also show that upstream dependencies without Python 3 support pose significant barriers in the adoption decisions of downstream packages: the cost of dealing with one Python 3-incompatible dependency is equivalent to, on average, one third of the cost of updating their source code. We also show by simulation that the network of packages contributes to 1.5 years "excess inertia" in 2018. "Excess intertia" refers to slow adoption even

[9]Our data comes from the Python Package Index project, which is the largest repository for Python packages. It records historical download information for more than 150,000 packages from 2005 onward.

though the majority of users benefit from the new technology (Farrell and Saloner (1985)).

The structural model allows us to conduct counterfactual exercises of "sponsorship". A sponsor is an entity willing to invest to promote a new technology, and can have an huge impact on the success of a new technology or standard (Katz and Shapiro (1986)) We evaluate the effectiveness of policies such as community-level targeted promotion of Python 3. Using modularity optimization tools developed in the social network literature, we group packages into various "communities" based on the dependency network: for example web development and data analysis communities. These communities differ significantly in their network structure. We test how technology adoption decisions can propogate such networks. We find that the effect of targeted community-level promotions have large heterogeneous effects on adoption rates due to differences in the network structure within a community. Moreover, promotion on one community has significant *positive or negative* effects on other connected communities. Our results imply that policies that take into consideration the network structure can significantly improve the effectiveness of promotion activities.

This paper contributes to the empirical literature estimating the effect of network structure on technology adoption decisions. Previous papers largely measured network effects using a "reduced-form approach" by modeling utility as the total number of users on the same network, and ignored the detailed linkages between individuals on a network. On the other hand, this paper also contribute to the literature of network analysis. Previous studies on network mainly adopted states models, whereas in reality, individuals are inherently dynamic and face intertemporal tradeoffs. Failure to control for forward looking agents can yield different estimation results and can misguide policy makers. (Rust (1987), Hendel and Nevo (2006), Gowrisankaran and Rysman (2012)) This paper is among the first to link the literature of dynamic discrete choice models to network analysis. It is the first to show how the input-output networks can lead to adverse effects on technology adoption process in a dynamic setting.

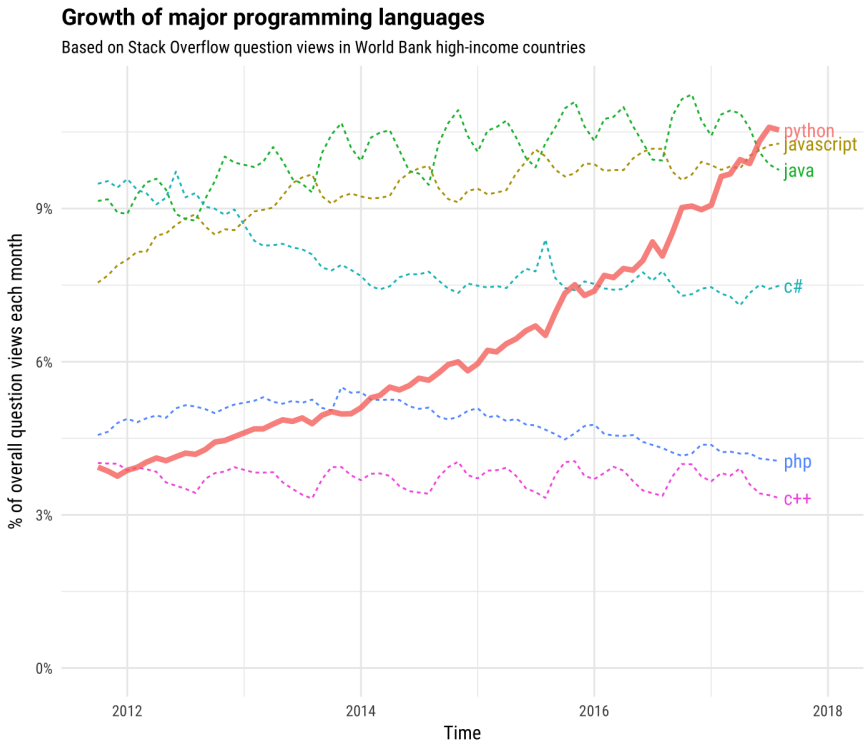


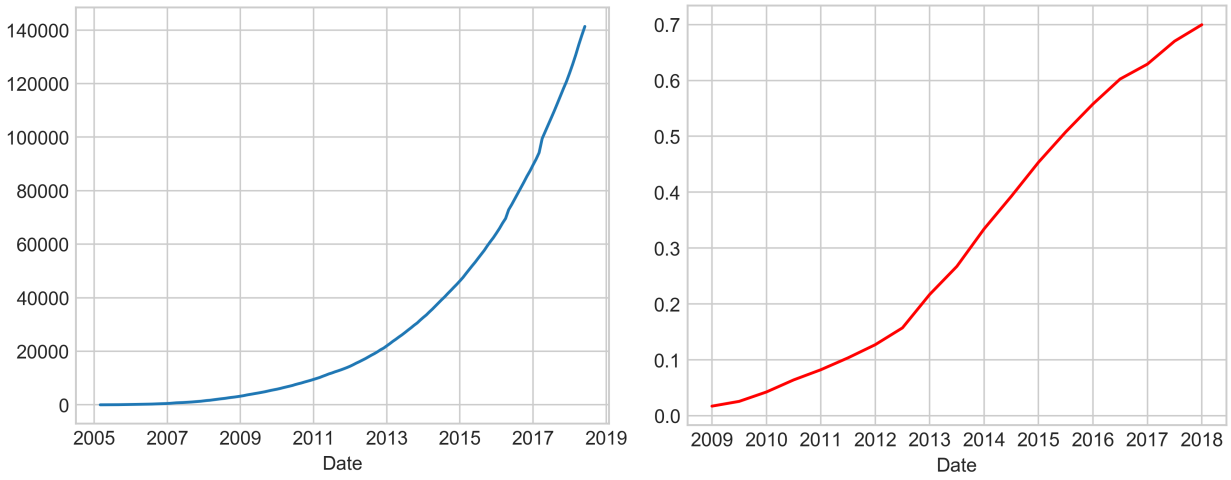
Figure 2: Popularity Trend of Programming Languages

2 Background: the Python Programming Language

Python is a general-purpose programming language.[10] It has a syntax that allows users to express concepts in fewer lines of code compared to most other languages, and it has been widely used in "Intro to Computer Science" courses in universities. The first version was released in 1989, but it did not gain much popularity until late 2000s. During the past few years, Python has become the fastest-growing major programming language. Figure 2 plots the numbers of visits to questions related to a particular programming language on Stack Overflow, the largest Q&A website for programming-related matters. Python has grown to be the number one based on this measure.

Backward compatibility has been a widely disputed topic in the software industry. The tradeoff is very clear: easier user transition to the new technology vs. higher cost of development and slowing innovation. In order to introduce several key features to Python, the

[10] A general-purpose programming language is a computer language that is broadly applicable across application domains. Examples of general-purpose programming languages include C, Java, and Python. It is in contrast to domain-specific language, such as MATLAB (numerical computing), Stata and R (statistical analysis), etc.



(1) Total Number of Packages

(2) % of Packages with Py3 Support

Figure 3: Python Packages with Python 3 Support

core teams decided to break the backward compatibility in a major release in 2008, namely, Python 3.[11] Users and package developers who would like to run their code on Python 3 would have to make sure that all the source code is compatible to Python 3.[12]

The transition process has indeed been longer than many had expected. Due to a large existing Python 2 user base, many packages are reluctant to provide Python 3 support. For those who did, they usually provide two versions for each release: one for Python 2, and another for Python 3 users.

Figure 3 plots the proportion of packages that provide Python 3 support. It has experienced a steady growth, during which timothy total number of packages has also been growing exponentially, indicating a growing popularity of Python programming language in general.

2.1 Motivation of Package Developers

Both the Python programming language and almost all the third-party packages are Open Source Software (OSS). The motivations of OSS contribution by software developers can be

[11]Some of the major new features include newer classes, Unicode encoding, and float division. Please refer to `http://python.org/` for more detailed information, and several examples of incompatibility are shown in Appendix 11.1

[12]Some packages are developed to help users to transit to Python 3 easier automatically. But in most cases, users and package developers would still have to test and manually modify much code.

Table 1: Package Characteristics

name	statsmodels
license	BSD
summary	Estimation and inference for statistical models
author	Josef Perktold, Chad Fulton, Kerby Shedden
version	0.9
requires_dist	numpy
	pandas
	matplotlib
classifiers	Intended Audience :: Science/Research
	Programming Language :: Python :: 2
	Programming Language :: Python :: 3
	Topic :: Scientific/Engineering

multifold. There are a large literature on the motivations behind private contributions to public goods such as Open Source Software.[13] Under any of the most common motivations (such as altruism, career, ego gratification, etc.), more downloads are always better for the developers.[14] Therefore, we assume that the payoff of package developers as a function of user downloads.[15]

3 Data

All of our data come from Python Package Index (PyPI). It is a repository of software for the Python programming language. In another word, it is a website packages can be stored and easily downloaded by users.

When uploading packages to PyPI, package developers usually provide various information related to the files, such as the description of the package, contact information of owner, whether they support for Python 2 or Python 3, what other packages are required as dependencies, etc. Table 1 lists some basic information related to a package. The dependency requirement comes from "requires_dist" section, and the Python 2/3 support status comes

[13]Nearly all the Python packages in our study are open source, which is also free of charge for anyone to use. A limited number of packages offer free downloads but requires payment for usage.

[14]von Krogh et al. (2012) and Xu, Nian, and Cabral (2016) provide overviews of the literature.

[15]Similar assumption has also been used in other papers in the study of OSS (See Gandal and Fershtman 2011 and Gandal and Stettner 2016).

Table 2: Downloads Statistics

(a) Before 2016: Cumulative Download

upload_time	2014-12-02
python_version	3.4
downloads	41564
filename	statsmodels-0.6.whl
size (bytes)	3969880

(b) After 2016: Individual Download

timestamp	2018-09-01
country_code	FR
filename	statsmodels-0.6.whl
project	statsmodels
version	0.6
python	3.4
system	Mac OS X

from "classifiers" section.[16]

User downloads data consists of two separate sources, both recorded by PyPI. Before 2016, cumulative download statistics for each file is recorded (as shown in Table 2.a). The system stopped working for a few months in early 2016 until May 2016, when PyPI introduced a brand new system hosted on Google BigQuery.[17] The new system records and publishes the characteristics of each individual download (as shown in Table 2.b). We combine the two sources of user downloads data and extrapolate the number of downloads for the missing time periods from January to May 2018.

Although there are currently more than 150,000 packages hosted on PyPI (as of September 2018), the vast majority are either abandoned or hobby projects for personal use. For example, 40% of all the packages have only 1 or 2 releases. Figure 4 plots the total downloads of top N packages as a percentage of all downloads in 2017. It shows a long tail of downloads across packages: top 100 packages account for about 58% of all downloads and top 500 packages account for 79% of all downloads.

For our analysis, we focus on packages that are well-maintained with regular releases. Thus, we select packages based on the following criteria (values in parenthesis are the unconditional percentage of packages that satisfy each measure):

- Time Duration (Last Release - First Release Date) $\geq$ 1 Year (12.9%)
- Downloads Per year $\geq$ 2000 (30.8%)

[16] In addition to the developer-provided information in the package description section, we also extract dependency requirement from the source files of each package and infer Python 2/3 support from filenames.

[17] Google BigQuery provides cloud-based data warehouse services. It can record large amount of data in real time, and provides end users easy access and manipulation of the stored data.

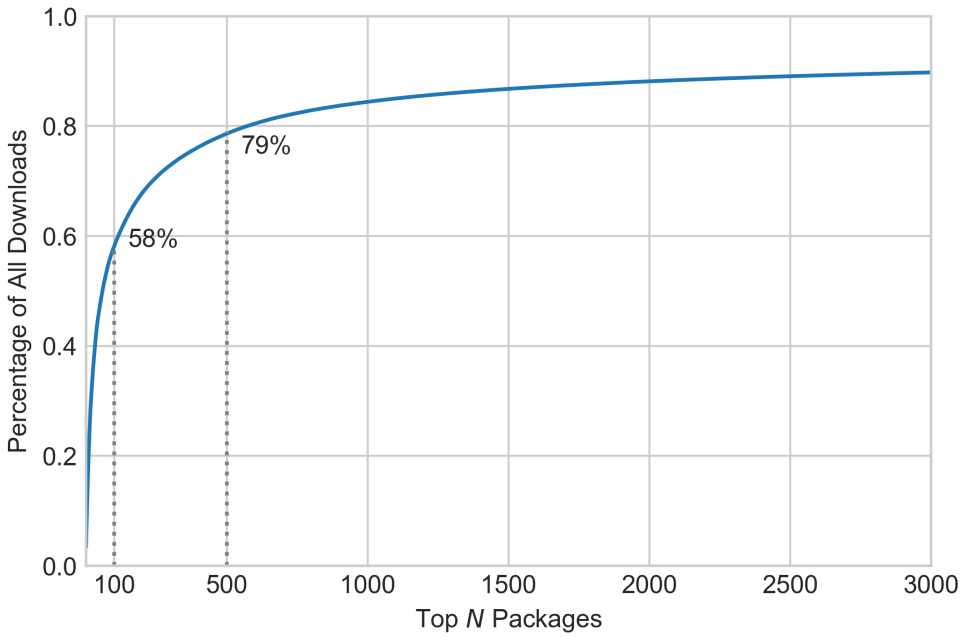


Figure 4: Total Downloads of Top Packages as Percentage of All Downloads

- Total Number of Releases ≥ 5 (38.9%)
- Total Releases / Time Duration ≥ 1 (92.4%)
- Some Python 2/3 Support Info Available (59.9%)

This selection criteria give us 4003 packages and 13056 observations for our analysis. Other selection measures will also be used for robustness checks.

Table 3: Summary Statistics

	All	Selected
Number of packages	143,584	4,005
Total downloads (in percentage)	100.00%	51.69%
Average logarithm of downloads per package	5.87	11.51
(min, max)	(0.0, 19.3)	(8.8, 19.3)
Average number of dependencies	0.72	3.12
(min, max)	(0, 174)	(0, 79)
Average logged package size (MB)	2.78	4.19
(min, max)	(0.0, 13.2)	(0.5, 10.6)

Table 3 shows the summary statistics of several key variables between the whole pop-

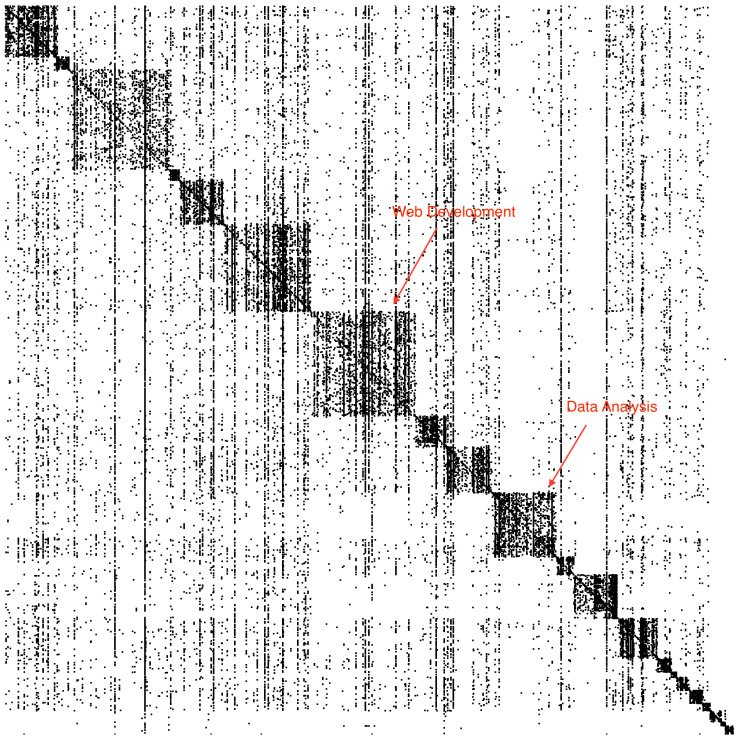


Figure 5: Python Community Through Dependency Network

ulation and our selected sample. The selected sample includes most of the most popular packages on Python, consisting 51.69% of all the downloads on PyPI. The average number of downloads for each package in the selected sample is also much higher than the whole population. On average, the selected sample has 3.12 dependencies, vs. 0.72 in the whole population. These packages are also larger in the file size. Consistent with other figures in this section, table 3 implies that our analysis focuses on those well-maintained packages with regular releases that faced a adoption decision of Python 3. These packages are also the most popular packages in the Python community.

All the decision and state variables in our model are measured in 6-month periods. For example, 2013/01/01 to 2013/06/30 is one period, and 2013/07/01 to 2013/12/31 is another.

3.1 Communities in Python

Python is a general-purpose programming language, meaning that it is not design for a specific community of users; rather, it is designed in a flexible way for the use by different communities (e.g. data analysis, web development, etc). The needs of communities are met

by third party packages, most of which are designed to achieve certain tasks in a specific field. Those packages that serve users of a given community tend to be more closely linked through dependencies. Using the latest heuristic method of modularity optimization, we are able to extract the community structure of the dependency network.

Figure 5 shows the 10 major communities through plotting a sparse matrix which represents the links between any two packages. Both x and y axes represent the packages. If two packages are linked, then there is a black dot. Therefore, each black square represents a community; a larger square means more packages in that community; a darker (or dense) one means packages in that community are more closely linked to each other.

3.2 Vertical Network with an Input-Output Representation

One particular characteristic of our model is the existence of the vertical network. Each package i has some linked with some upstream packages and downstream packages. Let use $\mathcal{G} \in \{0,1\}^n$ a $n \times n$ matrix to present the relationship between all packages. For each element $g_{i,j} \in \mathcal{G}$, if package j is a direct upstream package that has been cited in package i's report when releasing and appears in package i's source code, we would observe $g_{i,j} = 1$. We denote $\mathcal{U}_i = \{j;\, g_{i,j} \in j \; and \; g_{i,j} = 1\}$ the set of upstream firms. We assume in our paper that $\mathcal{G}$ is time-invariant and is commonly known by packages. Furthermore, elements in $\mathcal{G}$ are assumed to be arranged in row by their hierarchy, and there are in total L hierarchies. One can use block matrices to define $\mathcal{G}$:

$$\mathcal{G} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 \\ H_{2,1} & 0 & \cdots & \cdots & 0 \\ H_{3,1} & H_{3,2} & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 & 0 \\ H_{L,1} & H_{L,2} & \cdots & H_{L,L-1} & 0 \end{bmatrix},$$

where diagonal blocks and upper triangular part of the matrix $\mathcal{G}$ are zeros, block matrices $H_{i,j}$ for $i > j$ and $j = 2, ..., L$ represents the dependencies between packages in hierarchy i

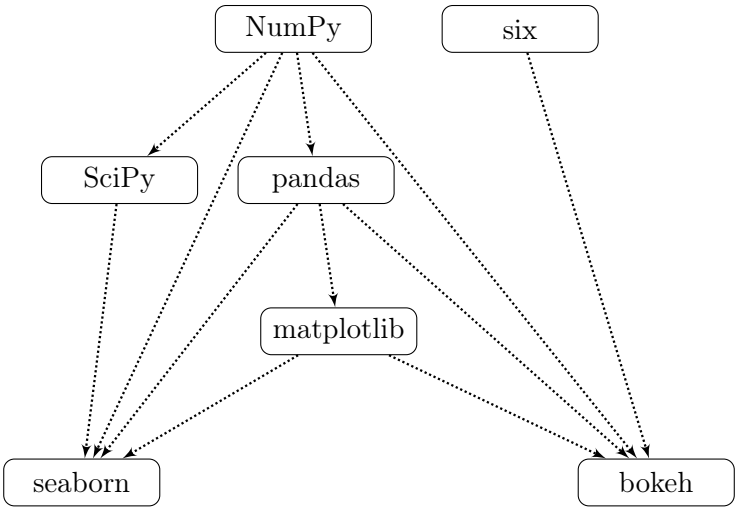


Figure 6: Example of Input-Output Network

and its upper hierarchy j. We further denote $\mathcal{H} = \{\mathcal{H}_1, ..., \mathcal{H}_L\}$ a set indicating the element's hierarchy level where $\mathcal{H}_\ell$ contains all packages belonging to hierarchy ℓ. For instance, if the network structure is defined as in Figure 6, we have:

$$\mathcal{G} = \begin{bmatrix} 0 & 0 & 0 \\ H_{2,1} & 0 & 0 \\ H_{3,1} & H_{3,2} & 0 \end{bmatrix} = \begin{matrix} a \\ b \\ c \\ d \end{matrix} \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

$$\mathcal{H} = \{\mathcal{H}_1, \mathcal{H}_2, \mathcal{H}_3\},$$

where $H_{2,1} = (1, 1)$ and $H_{3,1} = (0, 1)$, $H_{3,2} = 1$ and $\mathcal{H}_1 = \{A, B\}$, $\mathcal{H}_2 = \{C\}$, $\mathcal{H}_3 = \{D\}$. Furthermore, we have $\mathcal{U}_A = \mathcal{U}_B = \emptyset$, $\mathcal{U}_C = \{A, B\}$ and $\mathcal{U}_D = \{B, C\}$.

4 Model Setting

Our model is based on the single agent dynamic choice framework developed by Rust (1987) to analyze technology adoption decisions by packages of Python programming language. Each package i at time t can be described by a state variable $\mathcal{S}_{i,t}$. Given the current

state $\mathcal{S}_{i,t}$, each pkg i makes an irreversible decision to adopt Py3, namely, to make the pkg compatible to Py3.[18] Let $d_{i,t}$ be the a binary irreversible decision that she made, we have

$$d_{i,t} = \begin{cases} 1 & \text{if package } i \text{ adopts Python 3} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Packages are linked through dependency requirements. In order to incorporate the dependency network of packages and how packages affect each other through their adoption decisions, the state variable includes both one's own characteristics as well as those of dependencies. Thus, the state variable can be specified as the following:

$$\mathcal{S}_{i,t} = \Big\{ \underbrace{x_{i,t-1}}_{\substack{\text{user} \\ \text{downloads}}}, \underbrace{z_{i,t}}_{\substack{\text{other package} \\ \text{characteristics}}}, \underbrace{\epsilon_{i,t}^{d_{i,t}}}_{\substack{\text{i.i.d.} \\ \text{shocks}}}, \underbrace{d_{i,t-1}}_{\substack{\text{previous} \\ \text{adoption decision}}}, \underbrace{\{S_{j,t}, d_{j,t}\}_{j \in U_{i,t}}}_{\substack{\text{states and decisions} \\ \text{of dependencies}}} \Big\}.$$

The dependency network among packages is incorporated in the last component of the state variable. One implicit assumption is a sequential game play, i.e. package i observes the adoption decision made by its dependencies. Section 5.2 provides more discussion and implications on this assumption.

All the adoptions are irreversible, meaning that in each time period t, only packages without Python 3 support make the adoption decisions. The adoption decision comes with a one-time adoption cost, and it affects the transition dynamics of the state variable $\mathcal{S}_{i,t}$.

4.1 Value Function and Bellman Equation

Given the state $\mathcal{S}_{i,t}$, a package's flow utility can be written as:

$$u(S_{i,t}, d_{i,t}; \theta) - C(S_{i,t}, d_{i,t}; \theta) + \nu_{i,t}^{d_{i,t}} \tag{2}$$

$$= u(S_{i,t}, d_{i,t}; \theta) - \mathbf{1}(d_{i,t-1} = 0, d_{i,t} = 1)\, C(S_{i,t}; \theta) + \nu_{i,t}^{d_{i,t}}, \tag{3}$$

[18] More examples of irreversible decisions as well as discussion can be found in Rust and Phelan (1997) and Aguirregabiria and Mira (2010).

where $u(S_{i,t}, d_{i,t}; \theta)$ is the reward function of the indirect utility, which is a function of user downloads as discussed in Section 5.1. $C(S_{i,t}; \theta)$ is the one-time cost to adopt Python 3.

The value function for packages without Python 3 support can be written as the following dynamic problem:

$$V_\theta(\mathcal{S}_{i,t}, d_{i,t-1} = 0) \tag{4}$$

$$= \max_{\{d_{i,t+\tau}\}_{\tau=0}^{\infty}} \mathbf{E}_t \{ \sum_{\tau=0}^{\infty} \beta^\tau \Big(u(S_{i,t+\tau}, d_{i,t+\tau}; \theta) - D_{i,t+\tau} \, C(S_{i,t+\tau}; \theta) + \nu_{i,t+\tau}^{d_{i,t+\tau}} \Big) | \mathcal{S}_{i,t}; \theta \}. \tag{5}$$

The Bellmen equation implies at each period t, the ex ante value function, conditional on $d_{i,t-1} = 0$, can be represented by:

$$V_\theta(\mathcal{S}_{i,t}, d_{i,t-1} = 0) \tag{6}$$

$$= \max_{d_{i,t} \in \{0,1\}} u(S_{i,t}, d_{i,t}; \theta) - d_{i,t} \, C(S_{i,t}; \theta) + v_{i,t}^{d_{i,t}} + \beta \mathbf{E}_t V_\theta(\mathcal{S}_{i,t+1} | \mathcal{S}_{i,t}, d_{i,t}) \tag{7}$$

$$= \max\{ v_\theta(\mathcal{S}_{i,t}, d_{i,t-1} = 0, d_{i,t} = 0), v_\theta(\mathcal{S}_{i,t}, d_{i,t-1} = 0, d_{i,t} = 1) \} \tag{8}$$

$$= \max\{ u(S_{i,t}, d_{i,t} = 0; \theta) + v_{i,t}^0 + \beta \mathbf{E}_t V_\theta(\mathcal{S}_{i,t+1} | \mathcal{S}_{i,t}, d_{i,t} = 0), \tag{9}$$

$$u(S_{i,t}, d_{i,t} = 1; \theta) - C(S_{i,t}; \theta) + v_{i,t}^1 + \beta \mathbf{E}_t V_\theta(\mathcal{S}_{i,t+1} | \mathcal{S}_{i,t}, d_{i,t} = 1) \}. \tag{10}$$

The representation of value function for packages with Python 3 support is more straightforward, since the irreversibility condition implies that no further decisions are being made.

$$V_\theta(\mathcal{S}_{i,t}, d_{i,t-1} = 1) \tag{11}$$

$$= v_\theta(\mathcal{S}_{i,t}, d_{i,t-1} = 1, d_{i,t} = 1) \tag{12}$$

$$= \mathbf{E}_t \{ \sum_{\tau=0}^{\infty} \beta^\tau \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1 \Big) | \mathcal{S}_{i,t}; \theta \} \tag{13}$$

$$= \sum_{\tau=0}^{\infty} \beta^\tau \int \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1 \Big) dF_\theta(\mathcal{S}_{i,t+1} | \mathcal{S}_{i,t}). \tag{14}$$

We assume that $v_{i,t}^{d_{i,t}}$ are iid errors that follows Type 1 Extreme Value Distribution. Then the expected value function $\mathbf{E}_t V_\theta(\mathcal{S}_{i,t+1} | \mathcal{S}_{i,t}, d_{i,t})$ can be calculated using the following equation:

$$\mathbf{E}_t V_\theta(\mathcal{S}_{i,t+1}|\mathcal{S}_{i,t}, d_{i,t}=0) \tag{15}$$

$$= \int V_\theta(\mathcal{S}_{i,t+1}, d_{i,t}=0) dF_\theta(\mathcal{S}_{i,t+1}|\mathcal{S}_{i,t}, d_{i,t}=0) \tag{16}$$

$$= \int \log\{\sum_{d_{i,t+1}\in\{0,1\}} \exp(v_\theta(\mathcal{S}_{i,t+1}, d_{i,t}=0, d_{i,t+1}))\} dF_\theta(\mathcal{S}_{i,t+1}|\mathcal{S}_{i,t}, d_{i,t}=0) \tag{17}$$

$$\mathbf{E}_t V_\theta(\mathcal{S}_{i,t+1}|\mathcal{S}_{i,t}, d_{i,t}=1) \tag{18}$$

$$= \int V_\theta(\mathcal{S}_{i,t+1}, d_{i,t}=1) dF_\theta(\mathcal{S}_{i,t+1}|\mathcal{S}_{i,t}, d_{i,t}=1) \tag{19}$$

$$= \sum_{\tau=1}^{\infty} \beta^{\tau-1} \int \Big(u(S_{i,t+\tau}, d_{i,t+\tau}=1;\theta) + \nu^1_{i,t+\tau}\Big) dF_\theta(\mathcal{S}_{i,t+1}|\mathcal{S}_{i,t}, d_{i,t}=1). \tag{20}$$

Given the parameter θ and the transition dynamics described by F_θ, EV is iterated until convergence, which is then used to calculate choice-specific value functions $v_\theta(\mathcal{S}_{i,t}, d_{i,t-1} = 0, d_{i,t})$. The choice-specific value functions allow us to compute the predicted probability of adopting Python 3 using the standard logit formula:

$$P(d_{i,t}=1|\mathcal{S}_{i,t}, d_{i,t-1}=0;\theta) = \frac{v_\theta(\mathcal{S}_{i,t}, d_{i,t-1}=0, d_{i,t}=1)}{\sum_{d'\in\{0,1\}} v_\theta(\mathcal{S}_{i,t}, d_{i,t-1}=0, d')} \tag{21}$$

$$P(d_{i,t}=0|\mathcal{S}_{i,t}, d_{i,t-1}=0;\theta) = 1 - P(d_{i,t}=0|\mathcal{S}_{i,t}, d_{i,t-1}=0;\theta) \tag{22}$$

$$P(d_{i,t}=1|\mathcal{S}_{i,t}, d_{i,t-1}=1;\theta) = 1 \tag{23}$$

$$P(d_{i,t}=0|\mathcal{S}_{i,t}, d_{i,t-1}=1;\theta) = 0. \tag{24}$$

5 Parametrization & Transition Matrix

5.1 Payoff Function

As discussed in Section 2.1, we model the utility of package developers as a function of user downloads. Denote $x_{i,t}$ as the logrithm of total number of times a package i is downloaded by users in period t. We specify the payoff function as a linear function of user

downloads:

$$u(S_{i,t}, d_{i,t}; \theta) = \alpha^x \, x_{i,t}(x_{i,t-1}, d_{i,t}; \theta). \tag{25}$$

The evolution of $x_{i,t}$ relies on the package's adoption status/decision $d_{i,t}$. We assume that the evolution of the demand following a first-order Markov process:

$$x_{i,t} = \rho_0 + \rho_r \cdot d_{i,t} \cdot r_t + \rho_1 \cdot x_{i,t-1} + \upsilon_{i,t} \quad with \tag{26}$$

$$d_{i,t} = \begin{cases} 1 & \sum_{\tau \leq t} d_{i,\tau} = 1 \\ 0 & \sum_{\tau \leq t} d_{i,\tau} = 0 \end{cases}. \tag{27}$$

where d indicates if the package i has adopted before $t+1$, r_t is the current Python 3 adoption rate among all packages, $\upsilon^0_{i,t}$ and $\upsilon^1_{i,t}$ are two white noises that are normally and interdependently distributed with mean 0 and variances $\sigma^2_{d_0}$ and $\sigma^2_{d_1}$. [19]

The AR1 evolution of user demand is estimated outside the model of Python 3 adoption decisions by package developers. Then the estimates are used as input to the structural model.

The estimates of the AR1 demand equation essentially serves as the counterfactual demand for a package deciding whether to adopt Python 3. However, the estimates of the AR1 process might suffer from endogeneity problem. The AR1 process is estimated using the evolution of user downloads in a result of the actual adoption decision. Those packages who have adopted Python 3 might experience a positive persistent demand shock that is unobservable to the econometrician. In another word, due to the endogeneity issue, the benefit of Python 3 adoption inferred by the AR1 estimates can be over-exaggerated.

In order to control for the endogeneity, we introduce a two-step estimation approach using a synthetic instrumental variable. Given an initial AR1 estimates, first we estimate the model of technology adoption. Then in the second step, we use the predicted adoption probability as an instrumental for the endogenous variable $d_{i,t}$ and re-estimate the AR1 process. Then

[19] In the estimation of the user downloads function, we assume that package developers can perfectly predict the future values of r_t.

the new estimates are fed back to step 1 to re-estimate the model of technology adoption. Step 1 and 2 are conducted interactively until all the estimates converge to a fixed point. More discussions on identification can be found in Section 6.1.

5.2 Adoption Cost

We model the cost function as a function of agent's decision $d_{i,t}$, the number of coding lines (internal cost) $code_i$ and the network constraint $\mu_{i,t}$ that represents the number of dependencies without Python 3 support at time t, adjusted by an "importance" measure of that dependency. The switching cost is thereby defined as below:

$$C_{i,t} = AC_0 + \alpha^{\mu}\,\mu_{i,t}, \tag{28}$$

and we further assume that $\mu_{i,t}$ admits the following representation:

$$\mu_{i,t} = \sum_{j \in \mathcal{U}_i} \mathbf{1}\{d_{j,t} = 0\}. \tag{29}$$

$\mu_{i,t}$ is built as a raw measure of the adoption cost due to incompatible dependencies. In reality, such barrier might differ across different dependencies. For example, it might be much easier to find a dependency alternative to another small dependency compared to a large one. In the estimation stage, we also include $\mu^{adj}_{i,t} = \sum_{j \in \mathcal{U}_i} \mathbf{1}\{d_{j,t} = 0\} z_{j,t}$, that is, $\mu_{i,t}$ adjusted using the characteristics of the dependencies.

Assumption 1. *At time t, a package i observes Python 3 adoption decisions made by its dependencies, namely, $d_{j,t}$ for all $j \in U_{i,t}$.*

This is an assumption on the information set available to a package when making decisions. In particular, the question is that if a dependency $j \in U_{i,t}$ makes adoption decision at time t, would package i know it or not? If not, then it's more appropriate to model the game as a simultaneous-move game where the decisions are based on information from the previous period. If yes (as stated in Assumption 1), then it's more appropriate to model it

as a sequential-move game, and the downstream packages have better ideas of their adoption costs.

Assumption 1 simplifies our model estimation only slightly. Since the adoption cost comes from the dependencies without Python 3 support, at time t, a package i has to weigh the tradeoff between adopting today vs later, taking into consideration of the adoption probability of each of the Python 3-incompatible dependencies. With this assumption, the set of dependencies without Python 3 support at time t is weakly smaller, which can alleviate some computational burden in certain cases.

We prefer the latter setup for the following reasons: First, at any moment in time, a upstream package tend to have more public information available regarding the plans for future releases. A upstream package is usually much more popular compared to its downstream counterparts (in terms of downloads). They tend to pre-announce their plans for future releases, including Python 3 adoption decisions. Second, on the other hand, for a downstream package who wants to adopt Python 3 but faces incompatible dependencies, it's likely that it would pay more attention to such decision by its dependencies. In such a case, it is more likely that the Python 3 adoption decisions of upstream packages are available to downstream packages as soon as they are made.

Assumption 1 implies a sequential-move game where upstream packages make decisions first, followed by the downstream packages. The exact order of play in the model is defined based on the network structures, and it will be specified in detail in later sections.

We do not think that a simultaneous-move game (without Assumption 1) and a sequential one (with Assumption 1) would produce significantly different results. The only observations that can give rise to different estimates are cases when a package and its dependencies adopt Python 3 in the same time period, which are rare occasions in the data.

If package i observes $d_{j,t} = 1$, then the perceived AC is much smaller than the case without observing $d_{j,t}$. In this case, the cost parameter with a simultaneous-move model is underestimated compared to a sequential one.

5.3 State Variables & Transition Probability

As mentioned in the previous sections, one important component of the adoption cost comes from the dependency network when the dependency packages lack Python 3 support, which is represented by the last component of the state variables $\{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}$. We model a dynamic model of sequential decisions where upstream packages make adoption decisions before downstream packages, and downstream packages observe the decisions made by upstream packages at time t, namely $d_{j,t}$.

Package i cares about $\{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}$ in so far as it cares about its own adoption cost (a function of $\mu_{i,t}$), as well as its future evolution based given the current states. The law of motion of $\mu_{i,t}$ can be computed in the following way:

$$\begin{aligned} & \mathbf{P}(\mu_{i,t+1} = \mu' | \mu_{i,t} = \mu, \{d_{j,t}, \mathcal{S}_{j,t}\}_{j \in \mathcal{U}_{i,t}}; \theta) \\ = \ & \mathbf{P}(\mu' - \mu = \Delta\mu | \{d_{j,t}, \mathcal{S}_{j,t}\}_{j \in \mathcal{U}_{i,t}}; \theta), \end{aligned} \tag{30}$$

where $\Delta\mu$ is the change of the number of packages lacking Python 3 support from time t to $t+1$ and $\Delta\mu \in \{0, -1, -2, ..., -\mu\}$, i.e. adoption cost in future periods might be lower. Again, $\{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}})$ is important in predicting dependency j's probability of Python 3 adoption at a future date. Denote package i's belief that its dependency j will adopt Python 3 at time $t+1$ as $\widehat{p}^1_{j,t+1} = \mathbf{P}(d_{j,t+1} = 1 | d_{j,t} = 0, \mathcal{S}_{j,t}; \theta)$, and $\widehat{p}^0_{j,t+1} = \mathbf{P}(d_{j,t+1} = 0 | d_{j,t} = 0, \mathcal{S}_{j,t}; \theta)$.

Then we can write equation 30 as:

$$\mathbf{P}(\mu' - \mu = \Delta\mu | \{d_{j,t}, \widehat{p}_{j,t+1}\}_{j \in \mathcal{U}_{i,t}}; \theta). \tag{31}$$

With $\mu_{i,t} \equiv \sum_{j \in U_{i,t}} \mathbb{1}(d_{j,t} = 0)$, we can further simplify 31 by denoting the set of dependencies without Python 3 support as $\Omega_{i,t} \equiv \{j \in U_{i,t} | d_{j,t} = 0\}$, thus $\mu_{i,t} = |\Omega_{i,t}|$.

Then equation 31 can be written in the following way:

$$\mathbf{P}(\mu' - \mu = \Delta\mu | \{\widehat{p}_{j,t+1}\}_{j \in \Omega_{i,t}}; \theta). \tag{32}$$

The adoption decisions by different packages in $\Omega_{i,t}$ can lead to the same value of $\Delta\mu$.

Define $\mathcal{O}_{i,t}$ as the power set of $\Omega_{i,t}$ that contains all possible subsets of $\Omega_{i,t}$. Further we denote $\mathcal{O}_{i,t}^k = \{o \in \mathcal{O}_{i,t} \mid |o| = k\}$, i.e. all the elements of set $\mathcal{O}_{i,t}$ with the same cardinality of k.

Then equation 32 can be written as:

$$\sum_{o' \in \mathcal{O}_{i,t}^{\mu'}} \mathbf{P}(o' \mid \Omega_{i,t}, \{\widehat{p}_{j,t+1}\}_{j \in \Omega_{i,t}}; \theta) \tag{33}$$

$$= \sum_{o' \in \mathcal{O}_{i,t}^{\mu'}} \Big(\prod_{j \in o'} \widehat{p}_{j,t+1}^0 \prod_{j \in \Omega_{i,t} \setminus o'} \widehat{p}_{j,t+1}^1 \Big). \tag{34}$$

The burdensome mathmatical notation can be easily understood with a simple example. Suppose that at time t, package i has 3 dependencies $U_{i,t} = \{A, B, C\}$, and $d_{A,t} = 0$, $d_{B,t} = 0$, $d_{C,t} = 1$, leaving the set of dependency without Python 3 support being $\Omega_{i,t} = \{A, B\}$. Suppose package i's belief that each of the dependency will adopt Python 3 at time $t+1$ with the following probability: $\widehat{p}_{A,t+1}^1 = a$, $\widehat{p}_{A,t+1}^0 = 1 - a$, $\widehat{p}_{B,t+1}^1 = b$, $\widehat{p}_{B,t+1}^0 = 1 - b$. The powerset of $\Omega_{i,t}$ is $\mathcal{O}_{i,t} = \{\varnothing, \{A\}, \{B\}, \{A, B\}\}$, and $\mathcal{O}_{i,t}^0 = \{\varnothing\}$, $\mathcal{O}_{i,t}^1 = \{\{A\}, \{B\}\}$, $\mathcal{O}_{i,t}^2 = \{\{A, B\}\}$. Following equation 34, the transition from $\mu = 2$ to $\mu' = 1$ can be calculated as:

$$\sum_{o' \in \mathcal{O}_{i,t}^1 = \{\{A\},\{B\}\}} \Big(\prod_{j \in o'} \widehat{p}_{j,t+1}^0 \prod_{j \in \Omega_{i,t} \setminus o'} \widehat{p}_{j,t+1}^1 \Big) \tag{35}$$

$$= \prod_{j \in \{A\}} \widehat{p}_{j,t+1}^0 \prod_{j \in \{A,B\} \setminus \{A\}} \widehat{p}_{j,t+1}^1 + \prod_{j \in \{B\}} \widehat{p}_{j,t+1}^0 \prod_{j \in \{A,B\} \setminus \{B\}} \widehat{p}_{j,t+1}^1 \tag{36}$$

$$= \widehat{p}_{A,t+1}^0 \cdot \widehat{p}_{B,t+1}^1 + \widehat{p}_{B,t+1}^0 \cdot \widehat{p}_{A,t+1}^1 \tag{37}$$

$$= (1 - a)\, b + a\, (1 - b). \tag{38}$$

5.4 Transition Matrix

The calculation of EV in equation 17 depends crucially on the specification of the transition matrix, or $\mathbf{P}_{\mathcal{S}'|\mathcal{S}}$ in equation 17.

In our model, the utility function is mainly governed by two variables, namely, $x_{i,t}$,

the measure of downloads or popularity, and $\mu_{i,t}$, the measure of adoption cost due to dependencies. The construction of the transition matrix depends on the join law of motion of $x_{i,t}$ and $\mu_{i,t}$.

The law of motion of $x_{i,t}$ is relatively easy. We assume that it follows an AR1 process as specified in equation 26, with the parameter values estimated outside the value function iteration.

On the other hand, the law of motion of $\mu_{i,t}$ is much more difficult. $\mu_{i,t} \equiv \Omega_{i,t} \equiv \sum_{j \in U_{i,t}} \mathbb{1}(d_{j,t} = 0)$, i.e. the number of dependencies of package i without Python 3 support at time t.

One of the most important tradeoff for package i to adopt Python 3 today at t vs. future periods $t + \tau$ is the decreasing adoption cost due to the decreasing number of dependencies without Python 3 support over time. Therefore, the solution to the dynamic adoption model depends on the calculation of future adoption probabilities for each of the dependencies.

The calculation is a formidable task due to the nature of the nested dependency network. The computational difficulty can be illustrated by forecasting the Python 3 adoption probability for each of package i's dependency $j \in U_{i,t}$ at time $t + 1$:

$$\widehat{p}^1_{j,t+1} = \int_{\mathcal{S}_{j,t+1}} \mathbf{P}(d_{j,t+1} = 1 | \mathcal{S}_{j,t+1}, d_{j,t} = 0, z_j; \theta) d\mathbf{P}(\mathcal{S}_{j,t+1} | \mathcal{S}_{j,t}, d_{j,t} = 0, z_j; \theta). \tag{39}$$

The integral can then be computed through simulation of future states $\mathcal{S}_{j,t+1}$. Let $\mathcal{S}^m_{j,t+1}$ be the mth simulation, than the value of $\widehat{p^1_{j,t+1}}$ can be obtained by:

$$\widehat{p}^1_{j,t+1} = \frac{1}{M} \sum_{m=1}^{M} \mathbf{P}(d_{j,t+1} = 1 | \mathcal{S}^m_{j,t+1}, d_{j,t} = 0, z_j; \theta). \tag{40}$$

This simulation method can be very computationally intensive. Note that the nested states are expressed as $(x_{i,t-1}, d_{i,t-1}, \nu_{i,t}, \{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}})$. The simulation of the states of package j requires the simulation of the states of j's dependency $k \in U_{j,t+1}$, as well as the states of k's dependency, and so on. Any slight changes in any of the linked dependencies, or the dependencies of each dependency, can affect $p_{j,t}$. In this way, the full solution approach by Rust (1987) is no longer feasible due to the curse of dimensionality problem. In fact,

with the 3102 packages and 13056 observations, it is simpler to build the transition matrix dynamically for each package i at each time period t. In later sections 6 we list the detailed steps regarding how to compute $p_{j,t}$ for $j \in \Omega_{i,t}$ given the input-output network.

A transition matrix used for the dynamic programming problem includes the transition probability not only from the current state to the next, but also from each of the possible states to all other states. Given the state $S_{i,t}$, package i calculates $\widehat{p}^1_{j,t}$ for each of $j \in \Omega_{i,t}$. To construct the transition matrix, the belief of $\widehat{p}^1_{j,t+\tau}$ for $\tau \in \mathbb{N}$ is also needed.

Assumption 2. *Package i holds myopic expectations regarding the future Python 3 adoption probabilities by its dependencies, i.e. $\widehat{p}^1_{j,t+\tau} = \widehat{p}^1_{j,t}$ for all $\tau \in \mathbb{N}$.*

This assumption implies that although package i can correctly calculate the adoption probability of its dependencies at time t, the ability to forecast future probabilities is limited.

Assumption 2 greatly simplifies the model estimation. In a way, it bears certain similarity to the assumptions of inclusive value function, which is assumed to follow an AR1 process, in many previous papers (see Lee (2013) and Gowrisankaran and Rysman (2012)). In future version of this paper, we also plan to explore the possibility to allow the forecast of the adoption probability to follow such an AR1 process.

Combining the transition probability specified in equation 34 and Assumption 2, the full transition matrix needed to calculate $EV(S, d = 0; \theta)$ can be specified as the following:

$$P(o' \in O_{i,t} | o \in O_{i,t}) = \begin{cases} 0 & \text{if } o \nsubseteq o' \\ \prod_{j \in o'} \widehat{p}^0_{j,t} \prod_{j \in o \setminus o'} \widehat{p}^1_{j,t} & \text{if } o \subseteq o' \end{cases}. \tag{41}$$

The calculation of the transition matrix, as specified in equation 41, can be illustrated using the same example in section 5.3. Recall that the set of dependencies without Python 3 support is $\Omega_{i,t} = \{A, B\}$. The adoption probability of A and B at time t can be calculated by package i. Assume that $\widehat{p}^1_{A,t} = a$ and $\widehat{p}^1_{B,t} = b$. Assumption 2 implies that $\widehat{p}^1_{A,t+\tau} = a$ and $\widehat{p}^1_{B,t+\tau} = b$ for all $\tau \in \mathbb{N}$. The powerset of $\Omega_{i,t}$ is $\mathcal{O}_{i,t} = \{\varnothing, \{A\}, \{B\}, \{A, B\}\}$, and

$\mathcal{O}^0_{i,t} = \{\varnothing\}$. Therefore, the transition matrix of μ can be calculated using equation 41:

$$TM(\mu_{i,t}) = \begin{array}{c} \\ \{A,B\} \\ \{A\} \\ \{B\} \\ \varnothing \end{array} \begin{array}{c} \begin{array}{cccc} \{A,B\} & \{A\} & \{B\} & \varnothing \end{array} \\ \begin{bmatrix} (1-a)(1-b) & a(1-b) & (1-a)b & ab \\ 0 & 1-a & 0 & a \\ 0 & 0 & 1-b & b \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array}.$$

The corresponding value of μ for each row (or column) is 2,1,1,0, respectively. By construction, the transition matrix considers both the number and the identities of dependencies that are without Python 3 support. For example, the situation with dependency A being the only one without Python 3 support is different from the situation when B is the only one. Both cases have the same value of μ which is 1, thus having the same adoption cost, but the value of waiting is different because A and B have different likelihood of adoption in future periods. The transition matrix calculated using equation 41 takes cares of all such cases.

6 Identification & Estimation

6.1 Identification

In this section, we provide a brief discussion about the identification of our structural parameters.

The law of motion of x is modeled as a first-order Markov process, and it can be identified from the variation of x_t over time. Following the existing literature of dynamic discrete choice models (Keane (1994), Keane and Wolpin (1997)), we estimate $AR(1)$ separately from the structural model of technology adoption for computational purposes.

Once the law of motion of $x$is determined, one would be able to identify the fixed cost AC_0, α^μ through the predicted variation of $\Delta\mu$ as a function of (μ, x, d, θ).

In most setting of dynamic discrete choice models, the discount factor is typically assumed

and is not able to be separately identified from other parameters (Magnac and Thesmar (2002)). The identification of the discount factor requires variations that can shift expected discounted future utilities, but not current utilities (Abbring and Daljord (2018), De Groote and Verboven (2018)). We are able to identify the discount factor through the differences in dependency characteristics, which affect future values but not current utility. For example, two packages with the same characteristics and the same number but different dependencies have the same utility in the current period. However, the different dependencies have different future adoption probabilities, thus different transition matrix. If packages are myopic ($\beta = 0$), the two packages with different dependency characteristics should behave the same way; if packages are forward-looking ($\beta > 0$), larger differences in dependency characteristics should have a larger impact on the differences between the adoption probabilities of the two packages.

By assuming all packages share the same discount factor β, the variations of downloads allows us to identify α^x.

6.2 Estimation

Our model of technology adoption is estimated using Maximum Likelihood Estimation (MLE). The likelihood function is defined as:

$$l(\theta) = \prod_{i=1}^{N} \prod_{t=1}^{T_i} \widehat{p}_{i,t}^{0}{}^{\mathbf{1}\{d_{i,t}=0\}} \widehat{p}_{i,t}^{1}{}^{\mathbf{1}\{d_{i,t}=1\}},$$

where $\widehat{p}_{i,t}^{1} \equiv \widehat{p}^{1}(S_{i,t}; \theta)$, which is defined in equation 21.

6.3 Parameters

The parameters of interest in our model are the following:

$$\theta = \{\underbrace{\rho_0, \rho_1, \rho_r}_{\theta_D}; \ \underbrace{\alpha^x, AC_0, \alpha^\mu, \alpha^{size}, \beta}_{\theta_S}\}.$$

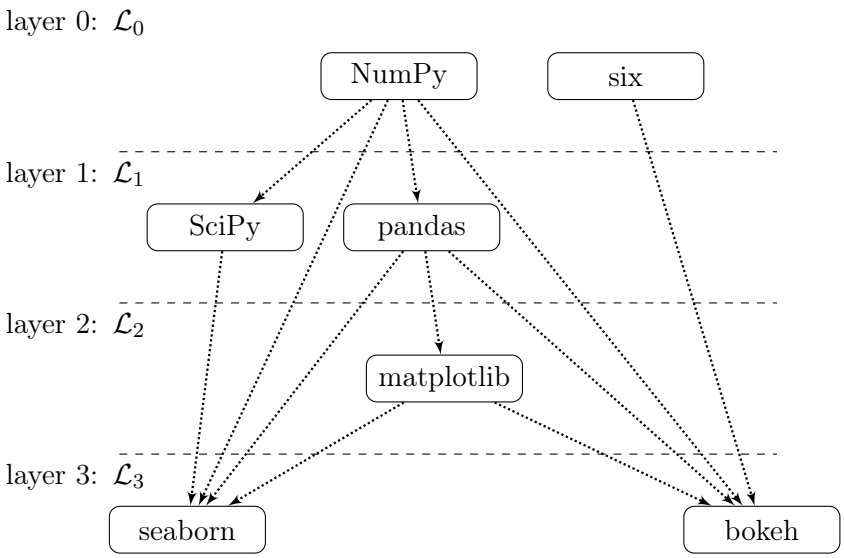


Figure 7: Layered Input-Output Network

It is convenient to group the parameters into θ_D and θ_S. θ_D includes parameters for the demand function, which is modeled as an AR1 process of user downloads; θ_S includes parameters for the supply side, which is the model of technology adoption.

6.4 Input-Output Network

The adoption decision of a package i depends crucially on the adoption status of its dependencies, which is summarized as $\mu_{i,t}$ in the utility function. Further, Assumption X states that $\mu_{i,t}$ is known to package i before making decisions at t. Assumption X allows us to model the adoption decisions sequentially. In every time period t, packages in layer 0 decide to adopt Python 3, followed by those in layer 1, then those in layer 2,..., etc. The probability of adopting Python 3 for each of the upstream packages is then used as given for the decision making process of the downstream package, in order to calculate the transition probability of $\mu_{i,t}$.

Through the dependency requirement, we group packages into different layers: $0, 1, 2, \cdots, L$. Figure 7 shows an example of the layered network. Each layer contains a set of packages with dependencies in the upstream layers. They can be grouped using the following iteration:

$$\mathcal{L}_0 = \{i \mid |U_i| = 0\}$$

$$
\begin{aligned}
\mathcal{L}_1 =& \{i \mid U_i \subseteq \mathcal{L}_0\} \\
\mathcal{L}_2 =& \{i \mid U_i \subseteq \mathcal{L}_{0,1}\} \\
&\vdots \\
\mathcal{L}_l =& \{i \mid U_i \subseteq \mathcal{L}_{0,1,\cdots,l-1}\} \\
&\vdots \\
\mathcal{L}_L =& \{i \mid U_i \subseteq \mathcal{L}_{0,1,\cdots,L-1}\}.
\end{aligned}
$$

where $\mathcal{L}_{0,1,\cdots,l} = \mathcal{L}_0 + \mathcal{L}_1 + \cdots + \mathcal{L}_l$

6.5 Estimation Procedure

Our algorithm begins by setting initial values for θ_D, which comes from OLS estimation of the AR1 process of user downloads, specified in equation 26. Estimation then involves iterating on four steps, where the mth iteration follows:

Step 1: Estimation of the Model of Technology Adoption

- Given estimates of demand function θ_D^m and initial guess of $\theta_S = \{\alpha^x, \alpha^\mu, AC_0\}$:
  - for $i \in \mathcal{L}_0$, build transition matrix for each i, t and calculate $\widehat{p}^1(\mathcal{S}_{i,t}; \theta)$
  - for $i \in \mathcal{L}_1$, given $\widehat{p}^1(\mathcal{S}_{j,t}; \theta) \quad \forall j \in \mathcal{L}_0$, build transition matrix for each i, t and calculate $\widehat{p}^1(\mathcal{S}_{i,t}; \theta)$
  - for $i \in \mathcal{L}_2$, given $\widehat{p}^1(\mathcal{S}_{j,t}; \theta) \quad \forall j \in \mathcal{L}_{0,1}$, build transition matrix for each i, t and calculate $\widehat{p}^1(\mathcal{S}_{i,t}; \theta)$

    $\vdots$
  - for $i \in \mathcal{L}_l$, given $\widehat{p}^1(\mathcal{S}_{j,t}; \theta) \quad \forall j \in \mathcal{L}_{0,1,\cdots,l-1}$, build transition matrix for each i, t and calculate $\widehat{p}^1(\mathcal{S}_{i,t}; \theta)$

    $\vdots$
  - for $i \in \mathcal{L}_L$, given $\widehat{p}^1(\mathcal{S}_{j,t}; \theta) \quad \forall j \in \mathcal{L}_{0,1,\cdots,L-1}$, build transition matrix for each i, t and calculate $\widehat{p}^1(\mathcal{S}_{i,t}; \theta)$

- Calculate likelihood fuction $l(\theta)$
- Update θ such that $\theta_S^{m+1} = \underset{\theta_S}{\text{argmax}}\, l(\theta_S, \theta_D^m)$

Step 2: Re-estimate Demand Using IV

- Given θ_D^m and θ_S^{m+1}, calculate the predicted adoption probability $\widehat{p}^1(\mathcal{S}_{i,t}; \theta_D^m, \theta_S^{m+1})$ for all i, t
- Re-estimate the AR1 process of demand function using $\widehat{p}_{i,t}^1$ as IV for $D_{i,t}$, and get a new set of estimates θ_D^{m+1} using the standard IV estimation method.

7 Preliminary Results

Table 4: Demand Estimation (AR1 Process)

	(1) OLS	(2) IV
(ρ_r) $d_{i,t} \times r_t$	0.165***	0.074***
	(0.01)	(0.01)
(ρ_1) $x_{i,t-1}$	0.898***	0.902***
	(0.00)	(0.00)
(ρ_0) Constant	1.069***	1.061***
	(0.02)	(0.02)
N	54230	54230
R^2	0.804	0.803

Table 4 reports the parameter estimates of the AR1 process of user downloads, specified in equation 26. Both OLS and IV estimation show that once a package adopts Python 3, the demand function process changes significantly.

For the same level of user DL $x_{i,t-1}$, OLS estimates predict a higher $x_{i,t}$ from Python 3 adoption than IV estimation does. The differences between OLS and IV estimates provides more clues of endogeneity. In reality, many packages adopt Python 3 even though having a low level of downloads, probably due to an unobserved positive download shock associated to Python 3, namely, a large $\epsilon_{i,t}^1$.

Table 5: Estimated Parameters of Adoption Model

Nonlinear	β	0.957***
Parameters (θ_S)		(0.196)
	α^x	0.690***
		(0.053)
	AC_0	-4.743***
		(0.713)
	α^μ	-0.310***
		(0.052)
	α^{size}	-0.219***
		(0.066)
Log Likelihood		-8019
Number of Packages		4005
Number of Observations		23267

Table 5 summarizes the estimation results of our model of technology adoption. All the coefficients are scaled by the variance of the error terms. The estimated discount factor 0.957 is equivalent to a monthly discount factor of 0.993, which is comparable to other papers in the literature (e.g. 0.988 in De Groote and Verboven (2018)). In future versions, we will provide more discussion on the identifiability of the discount factor. The coefficient of α^x, combined with the estimates in table 4, shows that developers benefit from more user downloads. The negative estimate of AC_0 shows a significant fixed adoption cost. Relative to the fixed cost, incompatible dependencies also serve as significant barriers to adoption. Note that the measure of $\mu_{i,t}$ used in the estimation is the number of incompatible dependencies weighted by the size of packages. The average size of a dependency is 4.89, thus, the average adoption cost due to one incompatible dependency is -1.516, which is roughly one-third of the estimated fixed cost.

8 Unobserved Heterogeneity

One concern related to the estimation results is sample selection bias due to unobserved heterogeneities. For example, package developers might have difference familiarities with Python 3, thus different adoption costs.

The presence of unobserved heterogeneities can bias the estimation results, because the

orthogonality assumption between the unobserved components and model inputs is violated. For example, more optimistic developers might also care more about the potential long-term benefits, which leads to an overestimation of α^x.

To deal with the unobserved heterogeneities, we employed the method developed by Belzil and Hansen (2002). We assume that the there are K types of packages. The probability of belonging to each type $k \in \{1, ..., K\}$ is defined as:

$$p_k = \frac{\exp(q_k)}{\sum_{j=1}^{K} \exp(q_j)} \; and \; q_K = 0.$$

The above equation allows to further rewrite the adoption probability $\hat{p}(\mathcal{S}_{j,t}; \theta)$ in Section 6.5 under the conditional probability:

$$\begin{aligned} \hat{p}(\mathcal{S}_{j,t}; \theta) &\equiv \hat{p}\left(\mathcal{S}_{j,t}; \theta, \{q_k\}_{k=1}^{K-1}\right) \\ &= \sum_{k=1}^{K} \hat{p}(\mathcal{S}_{j,t}|k; \theta, q_k) \times p_k. \end{aligned}$$

Table 6: Estimated Parameters of Adoption Model

Nonlinear	β	0.936***	
Parameters (θ_S)		(0.027)	
	α^x	0.854***	
		(0.221)	with probability
	AC_0 (type 1)	-3.513***	76.9%
		(0.447)	
	AC_0 (type 2)	-7.824***	23.1%
		(1.286)	
	α^{μ}	-0.328***	
		(0.025)	
	α^{size}	-0.114***	
		(0.042)	
Log Likelihood		-8010	
Number of Packages		4005	
Number of Observations		23267	

The method by Belzil and Hansen (2002) assumes that the type of each individual is implicit and randomly assigned. Table 6 reports the results of the estimation results with

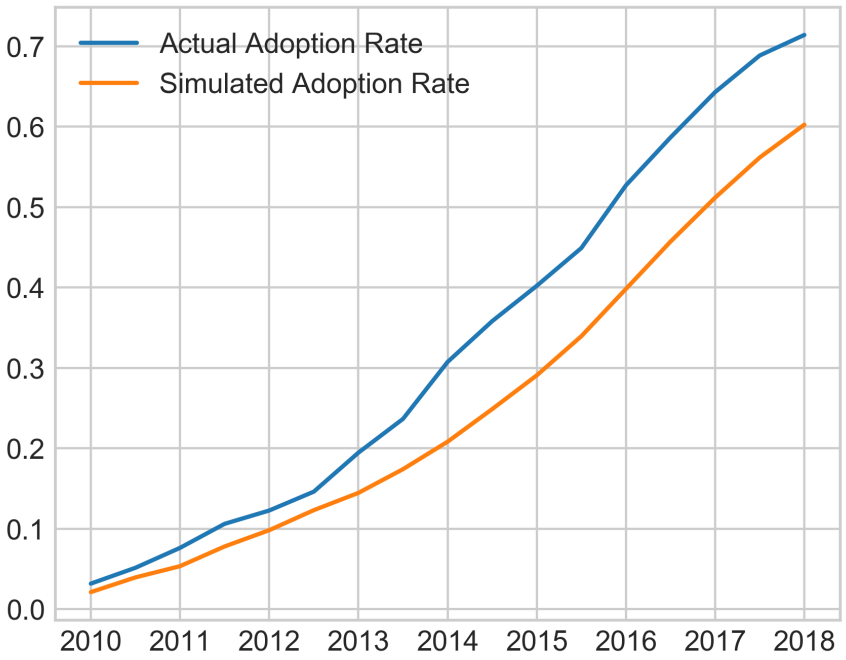


Figure 8: Actual vs. Simulated Adoption Rates

the presence of two hidden types ($K = 2$). We assume that there are two types because they naturally represent people who are optimistic about new technology and people who are pessimistic about new technology. We find that allowing for unobserved heterogeneity improves the model estimation, but not significantly. The value of the loglikelihood improves from -8019 to -8010.

Model estimation results with $K = 3$ and $K = 4$ are reported in the Appendix. The estimation results do not change with more unobserved types.

8.1 Model Prediction

One major advantage of structural model is the ability to run simulations. Through simulation, we can examine the goodness of fit of our model by comparing the actual versus simulated adoption rates over time. It can also be considered as cross validating our model by comparing auxiliary information from the data and the model.

Figure 8 plots the actual adoption rates against simulated adoption rates over time. The adoption rates is calculated as the percentage of packages with Python 3 support among the sample of 4005 packages used in the model estimation. The simulation is run using the

model without unobserved heterogeneity (column x in Table x).[20]

Our model predicts a slightly slower Python 3 adoption than the actual adoption decisions. We are currently working on several missing factors that might contribute to the under-prediction: 1. Unobserved heterogeneity (UH): UH can be incorporated in several variables such as the fixed cost AC_0, valuation of user downloads α^x, etc. 2. Selection: early adopters might be fundamentally different from late adopters in many ways. Our dynamic model can be enriched by adding the dimension of changing package types over time. 3. measurement errors in dependencies: the dependency information is provided by package developers when they upload their package to PyPI. Many packages with dependencies misreport their dependency requirements.

9 Counterfactuals

(Note: This section is still a work in progress. Some results might change in future versions.)

9.1 Network Effects on Adoption Rate

The model estimation shows that the adoption cost due to one additional incompatible dependency is equivalent to about one-third of the fixed cost. With the structural model, we examine the effect of the network on the speed of adoption through simulation. We simulate the adoption rates from the model with and without the channel of incompatible dependencies.

Figure 9 contrasts the simulated adoption rates with and without incompatible dependencies. It shows that the adoption cost due to incompatible dependencies contributes to about 1.5 years "inertia" to reach 60% adoption rate.

9.2 Community-Level Promotion

Katz and Shapiro (1985) predict that the success of a new technology and the speed of

[20] We are still working on simulation with unobserved heterogeneity.

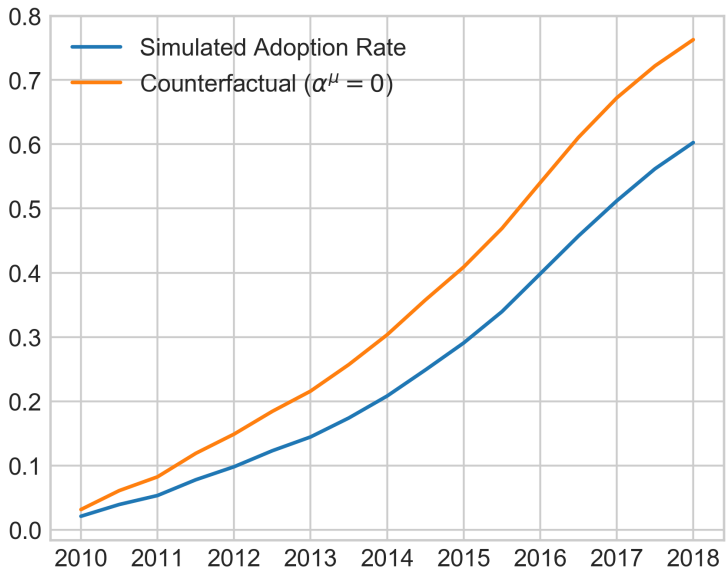


Figure 9: Simulated Adoption Rate Without Network Effects

technology adoption depends highly on the "sponsorship". A sponsor is an entity that is willing to make investment to promote it. The most important sponsor of Python is The Python Software Foundation (PSF). It is a nonprofit organization that oversees various issues in the Python community including the transition from Python 2 to 3. PSF has been promoting for a faster transition to Python 3. However, given the limited, probably exogenous amount of effort, it is key to understand how the effect can be spent most effectively in order to help the whole industry to switch to Python 3 at a fast pace.

One promotion policy we want to examine is the promoting Python 3 in different sub-communities. Within the Python community, there are many smaller communities based on the type of audience or domains. Network structure can differ significantly across these communities. Not only such differences can lead to different adoption patterns, they also react to counterfactual policies differently.

The differences in network structure can be seen both within- and across-communities. Packages in certain communities have more dense or central linkages compared others; packages in one community are also linked to other packages in a different community. Therefore, a community-level promotion of Python 3 can have a direct effect on that community and an indirect effect on other communities.

Table 7: Description of Python Communities

Community ID	Description
1	text processing & database
2	software development & security
3	website navigation & processing
4	software packing
5	data analysis
6	cryptography & security
7	command line interfaces & remote control
8	content management system
9	website building
10	others

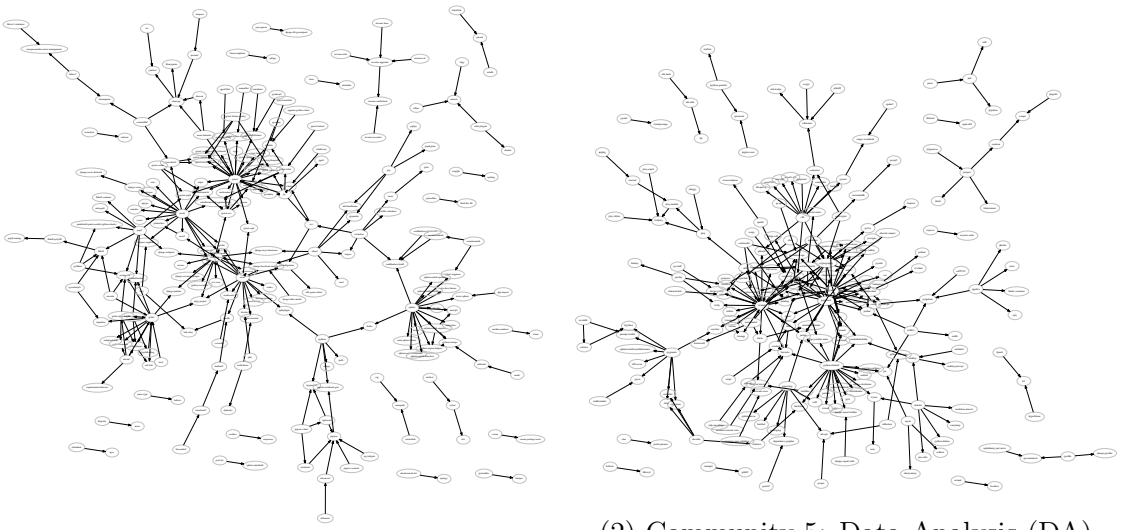
Table 8: Package Characteristics by Community

Community ID	Num. of Packages	Avg Logged Downloads	Avg Age (Years)	Avg Logged Package Size	Avg Num. of Dependencies	Avg Num. of Downstream Packages
1	317	8.442	4.243	3.996	2.389	18.040
2	357	8.687	4.162	3.894	3.393	10.529
3	397	8.150	3.914	3.474	2.605	25.977
4	274	8.702	4.527	3.765	3.623	18.718
5	388	8.154	4.208	5.347	2.785	30.549
6	204	8.786	4.389	4.171	2.827	20.833
7	207	8.280	3.967	3.956	2.727	5.833
8	288	7.877	6.305	4.606	4.751	18.130
9	567	8.326	4.458	3.847	2.407	11.987
10	1006	7.594	3.963	4.050	2.815	6.751

We cluster the 4,005 packages used in our model into 9 main communities. Table 7 and 8 describe the functionalities and characteristics of packages for each community. In the Appendix, Figure 12 plots the network structure for each of the 9 communities.

For example, we can see from the picture below, community 3 - Website Navigation (WN) and 5 - Data Analysis (DA) are two leading communities with similar statistics. WN has 397 packages (with 2.60 average dependencies) and DA has 388 packages (with 2.78 average dependencies). Each package in WN has on average 26 downstream packages, and DA has 31. However, these simple statistics cannot capture the detailed network structure.

Figure 10 plots the links of all the packages in WN and DA. It shows that DA has a more centralized network structure than WN.



(1) Community 3: Website Navigation (WN)

(2) Community 5: Data Analysis (DA)

Figure 10: Network Structure of Two Similar Communities

	1	2	3	4	5	6	7	8	9
1	6.18%	1.13%	-0.47%	-0.40%	0.95%	0.21%	1.08%	0.67%	0.62%
2	0.13%	6.87%	0.88%	0.09%	0.49%	0.05%	1.03%	0.27%	1.29%
3	0.85%	1.23%	7.06%	1.01%	0.77%	0.57%	0.83%	0.11%	-0.19%
4	1.63%	1.12%	1.03%	4.93%	0.90%	0.84%	1.66%	1.24%	1.97%
5	0.85%	1.14%	0.28%	0.05%	7.36%	1.57%	0.84%	2.20%	0.60%
6	1.34%	0.96%	-0.15%	0.64%	2.07%	6.56%	0.97%	-0.74%	-0.86%
7	-0.06%	0.82%	-0.23%	-0.55%	0.71%	0.17%	6.18%	0.91%	0.86%
8	-0.57%	0.12%	-0.35%	-0.32%	1.16%	0.41%	-0.05%	3.86%	0.22%
9	-0.10%	0.14%	1.21%	0.93%	-0.90%	0.93%	1.74%	0.20%	6.70%

Figure 11: Changes in Adoption Rate in 2017 with Community Promotion

We test the effectiveness of community-level promotion in order to promote a faster adoption process. We assume that the promotion can cause package developers in that particular community to change their expectation: once adopt Python 3, the number of user downloads would increase by an additional 10% permanently, on top of the additional downloads already captured by the time-varying AR1 process.

The effect of community-level promotion on changes in adoption rate in 2017 is plotted in Figure 11. Communites for each column mean the promoted community; communities for each row means the affected ones. For example, promotion activity targeted to community 1 results in 6.18% increase in adoption rate in community 1, 0.13% increase in community

2, 0.85% increase in community 3, etc.

The digonal items show that the direct effect of promotion within a community can have heterogeneous effects, ranging from 3.86% to 7.06%. Meanwhile, two similar communities with similar direct promotion effects might have very different indirect effects to other related communities.

Take the aforementioned example of community 3 - Website Navigation (WN) and 5 - Data Analysis (DA). Both communities have similar statistics (Table x) except the network structure (Figure x). The direct promotion effect is also similar. However, the indrect effect on other communities differ significantly. A promotion to DA can increase the adoption rate of community 5 - Cryptography & Security (CS) by 2.07%; whereas a promotion to 3 - WN reduces adoption in 5 - CS by 0.15%.

The adverse indirect impact on adoption rate could be due to the following channel: If a package anticipates that the dependencies would adopted in the near future, then it prefers to delay its own adoption. This channel shows that both the direct and indirect effect of promotion activities should be taken into consideration.

10 Conclusion

Technological changes have been fundamental to the economic growth. But many new technologies fail to attract quick and widespread adoption. In many cases, a fast adoption of new technologies can be socially beneficial: slow adoption often leads to long time of incompatible products, and a more rapid adoption enables consumers to better enjoy the convenience brought by the latest technology.

Economic theory has long proposed the barrier to adopt new technology due to existing network effects. Our research explores the ways technology adoption can be affected due to the network structure in a disaggregated input-output network. We find strong evidence that the adoption decisions of downstream players are significantly affected by their upstream counterparts.

This paper also developed a framework to measure the impact of such input-output network on technology adoption. We extend existing dynamic choice models to incorporate

a rich input-output network. Taking advantage of the unidirectional property of this network, we build and estimate a dynamic model that allow each agent to anticipate future actions of others. We believe that the structural framework can be applied to analyze other industries with such an input-output network structure.

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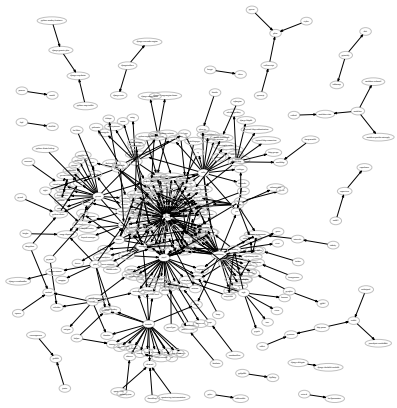
11 Appendix

11.1 Examples of Python 3 New/Incompatible Features

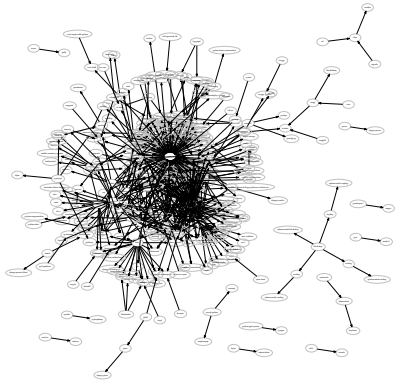
- Default Encoding System
  - Python 2: ASCII
    - e.g. “café” $\longrightarrow$ ’ascii’ codec can’t decode
    - solution: unicode(“cafÃ©”, encoding=’utf8’)
  - Python 3: Unicode
    - e.g. “café” $\longrightarrow$ café
    - unicode(“café”, encoding=’utf8’) $\longrightarrow$ ’unicode’ is not defined
- Division
  - e.g. $f(x) = \text{floor}(\frac{x}{2})$

	code	$x = 5$
Python 2	$x/2$	2
Python 2	$x//2$	2
Python 3	$x/2$	2.5
Python 3	$x//2$	2

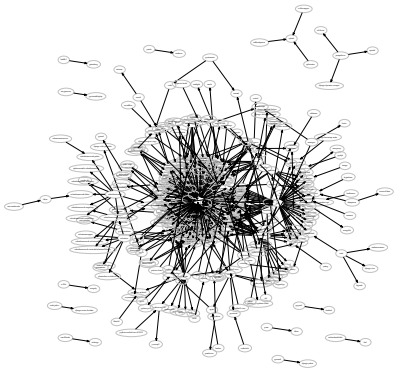
11.2 Network Structure of Python Communities



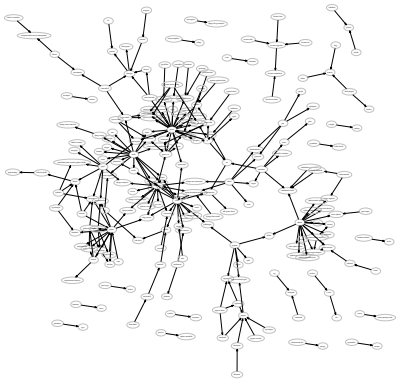
(1) text processing & database



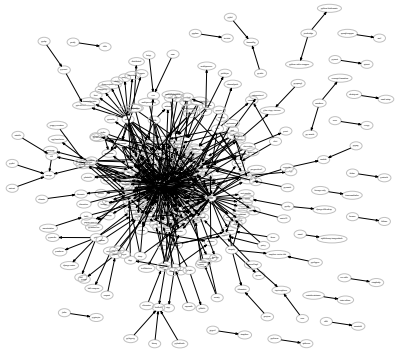
(2) software development & security



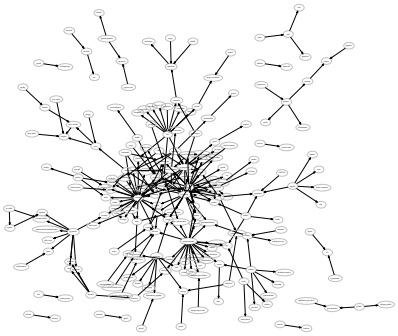
(3) website navigation & processing



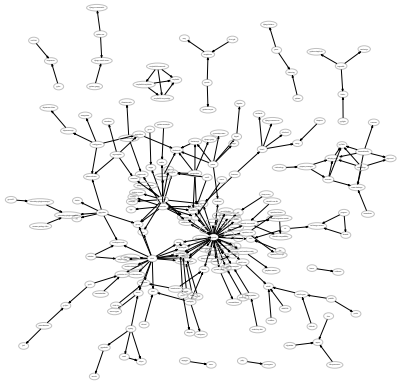
(4) software packing



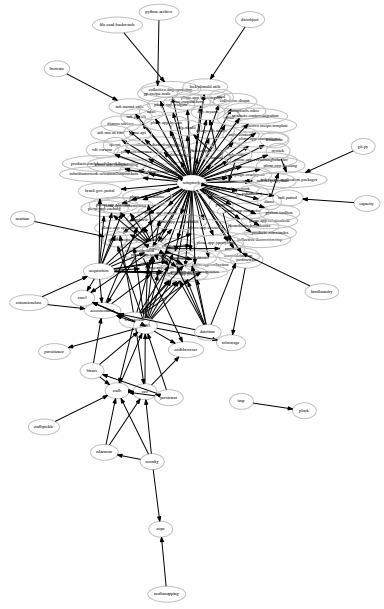
(5) data analysis



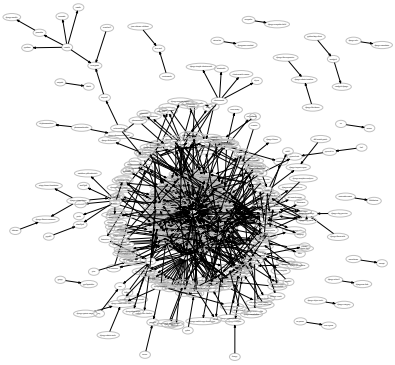
(6) cryptography & security



(7) command line interfaces & remote control



(8) content management system



(9) website building

Figure 12: Network Structure of Python Communities