# Techies, Productivity and Skill: Firm Level Evidence from France PRELIMINARY* 

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## 1 Introduction

Economists have been studying the nexus between labor demand, productivity, and technology adoption for decades. While there is a consensus that skill-biased technological change (SBTC) has raised the relative demand for more skilled workers, direct micro evidence supporting SBTC is remarkably sparse. One reason for this absence of evidence is that SBTC is devilishly difficult to measure. In this project, we propose a new way to identify technology adoption and to measure its skill bias. Our methodology has two broad components. The first is that we measure firm-level employment of the workers whose job it is to mediate technology adoption, whom we call techies. The second broad component is firm-level estimation of both Hicks neutral and skill augmenting productivity. We bring these two components together by estimating the causal effect of techies on productivity. Our preliminary results show that techies have a large effect on skill augmenting technology, which together with our production function estimates comprises direct evidence for SBTC at the firm level.

Our empirical approach has three pillars.

1. Administrative data on the entire French private sector economy. In addition to firm-balance sheet data, our data includes exceptionally detailed information on each firm's labor inputs. We exploit the detailed labor data in our research design.
2. An approach to estimating both neutral and non-neutral firm-level productivity that builds on recent developments in estimating firm-level productivity. Our approach uses the CES functional form along with the first-order conditions of firms' profit maximization problems to specify a structural equation which can be estimated.
3. A flexible specification of the firm's productivity process which permits us to make causal statements about the effects of firm's employment of workers in technical occupations ("techies") on firm productivity.

This rest of this document sketches our approach, and reports our preliminary results.

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## 2 Literature review

The papers most directly relevant to our project include Grieco et al. (2016), Doraszelski and Jaumandreu (2013), Doraszelski and Jaumandreu (2017), Bøler (2015), and Harrigan et al. (2016). The next draft of this paper will explain clearly the links between our work and these and other papers. Citations to discuss in the next draft include Helper and Kuan (2017) [they argue that engineers raise productivity in plants in automotive supply chain], Barth et al. (2017) [show that revenue per worker is higher in plants with techies], Kelly et al. (2014) [claim that industrial revolution occured in England instead of France because of higher human capital of English workers, in particular the stock of skilled workers who adopted and implemented new technology], De Loecker (2013) [for early/first discussion of correct estimation of models with endogenous Markov productivity]. Becker et al. (2013) [offshoring leads to skill upgrading within firms].

## 3 Econometric methodology

The standard approach to firm-level productivity estimation is to specify output as a function of inputs, develop an estimation methodology that identifies the parameters of the production function, and then back out the implied estimated productivity.

Our econometric methodology is tailored to the strengths and limitations of our data. Much of the econometric literature on production function estimation (including the foundational papers by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015)) has taken it as given that data on real inputs and outputs are available. In fact, this is almost never true: almost all datasets (including ours) include information on revenue $R_{f t}$ for firm $f$ in year $t$ and the value of expenditures on materials $M_{f t}$ but not data on the corresponding output and materials prices $p_{f t}^{Y}, p_{f t}^{M}$. De Loecker and Goldberg (2014) give a clear exposition of the estimation and interpretation problems that arise when real input and output quantities are unavailable. Grieco et al. (2016) (GLZ) show how to estimate the parameters of a CES production function even in the absence of real output or input data. Our approach extends GLZ in two ways. First, we separate labor into three components: skilled and unskilled labor $S$ and $L$, which contribute to output in the standard way, and workers $T$ in technical occupations ("techies") who are assumed to affect production only through their lagged impact on productivity. Second, we allow firm production functions within an industry to differ in two dimensions: through a Hicks neutral term $\Omega_{H f t}=e^{\omega_{H f t}}$ and a skilled-labor augmenting term $\Omega_{S f t}=e^{\omega_{S f t}}$.

### 3.1 Estimating productivity

We will discuss our unorthodox specification of the effect of techies on firm performance below. Here we begin with a CES function where physical output $Y_{f t}$ is produced using skilled labor $S_{f t}$, unskilled labor $L_{f t}$, capital $K_{f t}$, materials $M_{f t}$ and the two productivity levels. This function is assumed to be the same for all firms in an industry, which is to say that firms' production functions differ in their Hicks-neutral and skill-augmenting productivity levels but not in any other way. For reasons discussed by GLZ, it is important for identification to normalize each data series by its geometric mean, and we choose units/minimize notation such that the geometric means $\bar{L}=\bar{S}=\bar{K}=\bar{M}=\bar{Y}=1 .{ }^{1}$ Skilled labor services are the product of hours worked and skilled labor augmenting productivity $\Omega_{f t}^{S}$. The normalized production function is then

[^1]\[

$$
\begin{equation*}
Y_{f t}=\Omega_{H f t}\left[\alpha_{L} L_{f t}^{\gamma}+\alpha_{S}\left(\Omega_{S f t} S_{f t}\right)^{\gamma}+\alpha_{K} K_{f t}^{\gamma}+\alpha_{M} M_{f t}^{\gamma}\right]^{\frac{1}{\gamma}}, \gamma=\frac{\sigma-1}{\sigma} \tag{1}
\end{equation*}
$$

\]

Here, a positive skill-augmenting technology shock $\Omega_{S f t}$ has the interpretation of increasing the effective supply of skilled labor services holding hours worked constant. Similarly, the Hicks-neutral technology shock $\Omega_{H f t}$ shifts physical output holding all physical inputs and skill-augmenting technology constant. Input and output prices may differ across firms, but the researcher only observes revenue $R_{f t}$ and the value of materials purchases $E_{M f t}$, along with physical $L, S$ and $K$. The labor and materials inputs are assumed to be chosen after $\Omega_{H f t}$ and $\Omega_{S f t}$ are observed. The theory requirement $\sigma \geq 0$ implies $\gamma \leq 1$. To go from revenue to output requires an assumption on demand, and we follow GLZ in assuming that firms face a common, constant elasticity of demand $\eta<-1$. The inverse demand function facing the firm is very simple,

$$
\begin{equation*}
P_{f t}=A_{t} Y_{f t}^{\frac{1}{\eta}} \tag{2}
\end{equation*}
$$

where $A_{t}$ is an exogenous industry-level demand shifter. A revenue shock $u_{f t}$ is realized after all input choices have been made and both productivity levels have been realized. Revenue is thus given by

$$
\begin{equation*}
R_{f t}=e^{u_{f t}} P_{f t} Y_{f t}=e^{u_{f t}+\frac{\eta+1}{\eta} \omega_{H f t}} A_{t}\left[\alpha_{L} L_{f t}^{\gamma}+\alpha_{S}\left(\Omega_{S f t} S_{f t}\right)^{\gamma}+\alpha_{K} K_{f t}^{\gamma}+\alpha_{M} M_{f t}^{\gamma}\right]^{\frac{\eta+1}{\eta \gamma}} \tag{3}
\end{equation*}
$$

Equation (3) contains three unobservable shocks ( $u_{f t}, \omega_{H f t}$ and $\omega_{S f t}$ ) and one unobservable variable $M_{f t}$.

### 3.1.1 The estimating equation

Our approach to eliminating three of these four unobservables is to use economic theory. Since $L$, $S$ and $M$ are static, their first order conditions for expected ${ }^{2}$ profit maximization will always hold with equality:

$$
\begin{gather*}
\alpha_{L} L_{f t}^{-1 / \sigma} X_{f t}=W_{L f t}  \tag{4}\\
\alpha_{S} \Omega_{S f t}^{\gamma}\left(S_{f t}\right)^{-1 / \sigma} X_{f t}=W_{S f t}  \tag{5}\\
\alpha_{M} M_{f t}^{-1 / \sigma} X_{f t}=P_{M f t} \tag{6}
\end{gather*}
$$

where $X_{f t}=\left[\frac{1+\eta}{\eta}\right] A_{t} \Omega_{H f t}\left[\alpha_{L} L_{f t}^{\gamma}+\alpha_{S}\left(\Omega_{S f t} S_{f t}\right)^{\gamma}+\alpha_{K} K_{f t}^{\gamma}+\alpha_{M} M_{f t}^{\gamma}\right]^{\frac{\eta(1-\gamma)+1}{\gamma \eta}}$. Dividing (4) by (6) and solving for $M_{f t}$ gives

$$
\begin{equation*}
M_{f t}=\left(\frac{\alpha_{L}}{\alpha_{M}} \frac{E_{f t}^{M}}{E_{f t}^{L}}\right)^{1 / \gamma} L_{f t} \tag{7}
\end{equation*}
$$

where $E_{f t}^{M}=P_{M f t} M_{f t}$ is expenditures on materials and $E_{f t}^{L}=W_{L f t} L_{f t}$ is the unskilled labor wage bill. Dividing (4) by (5) and solving for $\Omega_{S f t}$ gives

[^2]\[

$$
\begin{equation*}
\Omega_{S f t}=\left(\frac{S_{f t}}{L_{f t}}\right)^{\frac{1}{\sigma-1}}\left(\frac{\alpha_{S} W_{f t}^{L}}{\alpha_{L} W_{f t}^{S}}\right)^{\frac{\sigma}{1-\sigma}} \tag{8}
\end{equation*}
$$

\]

Note that the derivation of (7) and (8) requires that $\sigma \neq 1$, which ironically is the Cobb-Douglas case that is the starting point for most of the productivity estimation literature. Next, substitute for $M_{f t}$ and $\Omega_{S f t}$ into the revenue function using (7) and (8) respectively,

$$
\begin{align*}
R_{f t} & =e^{u_{f t}+\frac{\eta+1}{\eta} \omega_{H f t}} A_{t}\left[\alpha_{L} L_{f t}^{\gamma}+\frac{\alpha_{L} E_{f t}^{S}}{E_{f t}^{L}} L_{f t}^{\gamma}+\alpha_{K} K_{f t}^{\gamma}+\frac{\alpha_{L} E_{f t}^{M}}{E_{f t}^{L}} L_{f t}^{\gamma}\right]^{\frac{\eta+1}{\eta \gamma}} \\
& =e^{u_{f t}+\frac{\eta+1}{\eta} \omega_{H f t}} A_{t}\left[\left(\frac{E_{f t}^{L}+E_{f t}^{S}+E_{f t}^{M}}{E_{f t}^{L}}\right) \alpha_{L} L_{f t}^{\gamma}+\alpha_{K} K_{f t}^{\gamma}\right]^{\frac{\eta+1}{\eta \gamma}} \tag{9}
\end{align*}
$$

Next, substitute (7) and (8) into (4), multiply both sides by $L_{f t}$ and solve for $e^{\frac{\eta+1}{\eta} \omega_{f t}}$ to get

$$
\begin{equation*}
e^{\frac{\eta+1}{\eta} \omega_{H f t}}=\frac{E_{f t}^{L}}{A_{t} \alpha_{L} L_{f t}^{\gamma}}\left[\frac{\eta}{1+\eta}\right]\left[\alpha_{L} L_{f t}^{\gamma}\left(\frac{E_{f t}^{L}+E_{f t}^{S}+E_{f t}^{M}}{E_{f t}^{L}}\right)+\alpha_{K} K_{f t}^{\gamma}\right]^{-\delta} \tag{10}
\end{equation*}
$$

which can be solved for Hicks-neutral productivity,

$$
\begin{equation*}
\omega_{H f t}=\frac{\eta}{1+\eta} \log \left\{\frac{1}{A_{t} \alpha_{L}} \frac{\eta}{1+\eta} L_{f t}^{-\gamma} E_{L f t} \times\left[\alpha_{L}\left(\frac{E_{L f t}+E_{f t}^{S}+E_{M f t}}{E_{L f t}}\right) L_{f t}^{\gamma}+\alpha_{K} K_{f t}^{\gamma}\right]^{\frac{-1}{\gamma}\left(\frac{\eta+1}{\eta}\right)}\right\} \tag{11}
\end{equation*}
$$

Plugging (10) into (9) and taking logs gives the estimating equation,

$$
\begin{equation*}
\ln R_{f t}=\ln \left[\frac{\eta}{1+\eta}\right]+\ln \left[E_{f t}^{S}+E_{f t}^{M}+E_{f t}^{L}\left\{1+\frac{\alpha_{K}}{\alpha_{L}}\left(\frac{K_{f t}}{L_{f t}}\right)^{\gamma}\right\}\right]+u_{f t} \tag{12}
\end{equation*}
$$

Our estimating equation (12) has just three parameters ( $\eta, \gamma$ and $\alpha_{K} / \alpha_{L}$ ), and as in GLZ it can be estimated by nonlinear least squares. The key to the derivation is that there are three static inputs ( $S, L$ and $M$ ), which gives us two ratios of static first order conditions, (7) and (8). These two equations allow us to eliminate the two unobservables, $M_{f t}$ and $\Omega_{S f t}$, and (10) allows us to eliminate $\Omega_{H f t}$.

The model has six parameters of interest $\left(\eta, \gamma, \alpha_{S}, \alpha_{L}, \alpha_{K}\right.$ and $\left.\alpha_{M}\right)$. The remaining three parameters are identified by the following equations,

$$
\begin{gather*}
\alpha_{L}+\alpha_{S}+\alpha_{K}+\alpha_{M}=1  \tag{13}\\
\alpha_{M} \bar{E}^{L}=\alpha_{L} \bar{E}^{M}  \tag{14}\\
\alpha_{S} \bar{E}^{L}=\alpha_{L} \bar{E}^{S} \tag{15}
\end{gather*}
$$

Equation (13) is an implied by the identity that factor shares sum to one. Equations (14) and (15) follow by taking the geometric means of (7) and (8) respectively, and using the normalization conditions.

### 3.1.2 Recovering productivity

Once this estimator is implemented, we can recover estimated Hicks neutral and skill augmenting productivity using (11) and (8) respectively. Fully recovering Hicks neutral productivity also requires an estimate of the unobservable aggregate $A_{t}$. This doesn't matter for the cross sectional distribution at a point in time, but it does imply that our Hicks neutral productivity estimates are comparable over time only in relative terms. That is, we can compare two firm's productivity in a given year, and we can say how this comparison changes over time, but we cannot compare productivity for a given firm over time.

### 3.2 Endogenous productivity

In the OP/LP/ACF methodology, productivity is treated as completely exogenous. But one reason to do firm-level productivity estimation (and one of our motivations) is to be able to study what causes the estimated productivity differences. In the trade literature, this has been done repeatedly in the context of explaining the fact that exporters have higher productivity: is this fact due to selection à la Melitz (2003), or is there an additional causal "learning-by-exporting" effect? A key contribution of De Loecker (2013) is to clarify how to answer this question, though his estimator can be generalized.

In estimating productivity in section 3.1 , we made no assumptions about the stochastic processes that characterize productivity. Because of this, we are free to study the determinants of productivity in a flexible way, using firm-level explanatory variables. Following Doraszelski and Jaumandreu (2013), we now assume that productivity is given by a "controlled Markov" process, where productivity depends on three factors:

1. lagged productivity
2. variables chosen by the firm, and
3. a shock which is orthogonal to all the other shocks in the model.

In this preliminary draft, we assume that the only firm-level determinant of productivity is lagged employment of techies, $T_{f t-1}$. To allow $\omega_{H f t}$ and $\omega_{S f t}$ to influence each other we specify the following two equation system,

$$
\begin{gather*}
\omega_{H f t}=\beta_{H t}+\beta_{H H} \omega_{H f t-1}+\beta_{H S} \omega_{S f t-1}+\beta_{H T} T_{f t-1}+\xi_{H f t}  \tag{16}\\
\omega_{S f t}=\beta_{S t}+\beta_{S H} \omega_{H f t-1}+\beta_{S S} \omega_{S f t-1}+\beta_{S T} T_{f t-1}+\xi_{S f t} \tag{17}
\end{gather*}
$$

The shocks $\xi_{H f t}$ and $\xi_{S f t}$ are assumed to be statistically independent. The time fixed effects $\beta_{H t}$ and $\beta_{S t}$ control for among other things the demand shifter $A_{t}$. These equations can be consistently estimated by OLS. Following De Loecker (2013) and Doraszelski and Jaumandreu (2013), in future drafts we will also estimate more general non- or semi-parametric versions of (16) and (17), and include indicators of lagged firm-level trade on the right hand side. A virtue of the parametric specification given by (16) and (17) is that it is straightforward to calculate the steady-state crosssectional effects of persistent differences in techies,

$$
\left[\begin{array}{c}
\omega_{H f} \\
\omega_{S f}
\end{array}\right]=(I-B)^{-1} T_{f}, \quad B=\left[\begin{array}{cc}
\beta_{H H} & \beta_{H S} \\
\beta_{S H} & \beta_{S S}
\end{array}\right]
$$

It is important to be clear about what is meant by a "controlled Markov process". The key is that the Markov assumption breaks realized productivity into expected and unexpected components. Thus statistical exogeneity of lagged productivity and techies in (16) and (17) is assured, but can we interpret the estimated effects of (say) techies as causal in the cross section? For example, if $\beta_{H T}>0$, can we say "techies cause higher Hicks-neutral productivity"? If the answer is yes, that raises the question, what determines the choice of techies, and why don't all firms choose the same level of techies? The same goes for including lagged trade indicators in (16) and (17) in future drafts. In the trade context, underlying differences in firm-specific trade costs have been used to explain why not all firms export, and similar reasoning can be applied in the case of techies: some products/processes are simply harder to improve using ICT, and/or firms have unobservable heterogeneity in their aptitude for applying IT and thus employing techies.

De Loecker (2013) page 8 has a persuasive discussion of how to interpret the learning-byexporting effect in his version of the controlled Markov process. He emphasizes two things. One, it is lagged exporting that enters the Markov process, which is to say that productivity (more precisely, the shock to productivity $\xi_{H f t}$ ) is realized after the exporting decision is made. Two, the persistence of the exporting decision is controlled for by having lagged realized productivity in the equation for current productivity. These arguments extend directly to our setting.

The way that Doraszelski and Jaumandreu (2013) discuss their estimated effects of R\&D on productivity is to punt on the issue of how R\&D decisions are decided. That is, they answer the question: given that a firm has decided to do R\&D, what is the estimated effect on productivity? We will take the same approach, and will interpret our estimates as answering the question: given that a firm has decided to employ techies, what is the estimated effect on productivity?

## 3.3 the effect of techies on output

A central element of our methodology is that we assume that techies affect output only through their effect on future productivity, and not through any contemporaneous contribution to factor services that affect current output. This assumption is analogous to the standard assumption that investment in $t-1$ has no effect on output in $t-1$, but raises output in $t$ through its contribution to $K_{t}$. Our reasons for specifying the role of techies in this way are both theoretical and empirical. Theoretically, if techies affect both current output through their presence as part of skilled labor $S_{t}$ and future productivity via equations (16) and (17), then the static first order condition (5) would not hold and the derivation of our estimating equation (12) does not go through. Empirically, if techies enter the production function (1) as a separate factor, an implication is that employment of techies would be strictly positive for all firms in all periods, which is emphatically not the case [cite incidence of techies in our sample].
\{discuss empirical rationale for our specification, including Helper and Kuan (2017) and Barth et al. (2017) and Bresnahan et al. (2002) and Tambe and Hitt (2014) \}.

For implications of misspecification, see "Notes on identifying non-neutral firm level productivity.lyx". This should be incorporated into this document.

While our assumption that techies affect output only through their effect on future productivity is well-grounded, it is important to consider how our measurement of productivity could go awry if techies do in fact increase current output directly, a case that we will call the "orthodox model". For concreteness, we suppose that in the orthodox case techies are a component of skilled labor $S$, so that that techies $T$ and managers $B$ (for "bosses") together make up skilled labor $S$, and that the techie share varies across firms and time. In levels, this assumption amounts to

$$
S_{f t}=T_{f t}+B_{f t}=\delta_{f t} B_{f t}+B_{f t}=\left(1+\delta_{f t}\right) B_{f t}
$$

Using the approximation $\log \left(1+\delta_{f t}\right) \simeq \delta_{f t}$ gives $s_{f t}=\delta_{f t}+m_{f t}$. Similarly, define $\lambda_{f t}$ as the techie share of the wage bill of $S$,

$$
E_{f t}^{S}=E_{f t}^{T}+E_{f t}^{B}=\left(1+\lambda_{f t}\right) E_{f t}^{B}
$$

The expressions for Hicks-neutral and skill-augmenting productivity in the orthodox model respectively are

$$
\begin{gather*}
\omega_{f t}^{H}=\frac{\eta}{1+\eta} \log \left\{\frac{1}{A_{t} \alpha_{L}} \frac{\eta}{1+\eta} L_{f t}^{-\gamma} E_{L f t} \times\left[\alpha_{L}\left(\frac{E_{L f t}+E_{f t}^{S}+E_{M f t}}{E_{L f t}}\right) L_{f t}^{\gamma}+\alpha_{K} K_{f t}^{\gamma}\right]^{\frac{-1}{\gamma}\left(\frac{\eta+1}{\eta}\right)}\right\}  \tag{18}\\
\omega_{f t}^{S}=l_{f t}-s_{f t}+\frac{1}{\gamma} l o g\left(\frac{\alpha_{L} E_{f t}^{S}}{\alpha_{S} E_{f t}^{L}}\right) \tag{19}
\end{gather*}
$$

### 3.3.1 implications of misspecification for measuring Hicks-neutral productivity

Under the assumption that our model is correct, we can write true Hicks-neutral productivity as

$$
\begin{equation*}
\omega_{f t}^{H 1}=\frac{\eta}{1+\eta} \log \left\{\frac{1}{A_{t} \alpha_{L}} \frac{\eta}{1+\eta} L_{f t}^{-\gamma} E_{L f t}\right\}-\frac{1}{\gamma} \log \left\{\alpha_{L}\left(\frac{E_{L f t}+E_{f t}^{B}+E_{M f t}}{E_{L f t}}\right) L_{f t}^{\gamma}+\alpha_{K} K_{f t}^{\gamma}\right\} \tag{20}
\end{equation*}
$$

Under the assumption that the orthdox model is correct,
$\omega_{f t}^{H 2}=\frac{\eta}{1+\eta} \log \left\{\frac{1}{A_{t} \alpha_{L}} \frac{\eta}{1+\eta} L_{f t}^{-\gamma} E_{L f t}\right\}-\frac{1}{\gamma} \log \left\{\alpha_{L}\left(\frac{E_{L f t}+\left(1+\lambda_{f t}\right) E_{f t}^{B}+E_{M f t}}{E_{L f t}}\right) L_{f t}^{\gamma}+\alpha_{K} K_{f t}^{\gamma}\right\}$
If we assume that the orthdox model is correct, but incorrectly estimate Hicks-neutral productivity using $\omega_{f t}^{H 1}$, then the error is
$\omega_{f t}^{H 1}-\omega_{f t}^{H 2}=\frac{1}{\gamma}\left[\log \left\{\alpha_{L}\left(\frac{E_{L f t}+\left(1+\lambda_{f t}\right) E_{f t}^{B}+E_{M f t}}{E_{L f t}}\right) L_{f t}^{\gamma}+\alpha_{K} K_{f t}^{\gamma}\right\}-\log \left\{\alpha_{L}\left(\frac{E_{L f t}+E_{f t}^{B}+E_{M f t}}{E_{L f t}}\right) L_{f t}^{\gamma}+c\right.\right.$
This expression is clearly strictly positive and increasing in the techie share $\lambda_{f t}$. The intuition is clear: the larger is $\lambda_{f t}$, the greater is the underestimate of true inputs under the wrong model and thus the greater the overestimate of Hicks-neutral productivity.

### 3.3.2 implications of misspecification for measuring skill-augmenting productivity

Under the assumption that our model is correct, we can write true skill-augmenting productivity as

$$
\omega_{f t}^{S 1}=l_{f t}-b_{f t}+\frac{1}{\gamma} \log \left(\frac{\alpha_{L} E_{f t}^{B}}{\alpha_{B} E_{f t}^{L}}\right)
$$

Under the assumption that the orthdox model is correct, and using $\log \left(1+\lambda_{f t}\right) \simeq \lambda_{f t}$, we can write true skill-augmenting productivity as

$$
\begin{aligned}
\omega_{f t}^{S 2} & =l_{f t}-b_{f t}-\delta_{f t}+\frac{1}{\gamma} \log \left(\frac{\alpha_{L}\left(1+\lambda_{f t}\right) E_{f t}^{B}}{\alpha_{S} E_{f t}^{L}}\right) \\
& =l_{f t}-b_{f t}-\delta_{f t}+\frac{\lambda_{f t}}{\gamma}+\frac{1}{\gamma} \log \left(\frac{\alpha_{L} E_{f t}^{B}}{\alpha_{S} E_{f t}^{L}}\right)
\end{aligned}
$$

If we assume that the orthdox model is correct, but incorrectly estimate skill-augmenting productivity using $\omega_{f t}^{S 1}$, then the error is

$$
\omega_{f t}^{S 1}-\omega_{f t}^{S 2}=\delta_{f t}-\frac{\lambda_{f t}}{\gamma}+\frac{1}{\gamma} \log \left(\frac{\alpha_{S}}{\alpha_{B}}\right)
$$

The third term in this expression is a constant, while the first is positive. In our application we always estimate $1>\gamma>0$, so the second term is negative. If techies are paid on average the same as managers, then $\delta_{f t}=\lambda_{f t}$ and we have

$$
\omega_{f t}^{S 1}-\omega_{f t}^{S 2}=\delta_{f t}\left(\frac{\gamma-1}{\gamma}\right)+\frac{1}{\gamma} \log \left(\frac{\alpha_{S}}{\alpha_{B}}\right)
$$

Since $\left(\frac{\gamma-1}{\gamma}\right)<0$, we conclude that the error is negatively correlated with the techie share in the cross section: firms with high techie shares will have measured skill-augmenting productivity which is biased down by more than firms with low techie shares. With $1>\gamma>0$ and $\alpha_{S}>\alpha_{B}$, the constant term $\frac{1}{\gamma} \log \left(\frac{\alpha_{S}}{\alpha_{B}}\right)$ is positive.

## 4 Data

We combine two confidential firm-level administrative datasets to study the French private sector economy between 2000 and 2013.

### 4.1 Workers: DADS Poste

Our source for information on workers is the DADS Poste, which is based on mandatory annual reports filed by all firms with employees, so our data includes all private sector French workers except the self-employed. ${ }^{3}$ Our unit of analysis is annual hours paid in a firm, by occupation. The data is reported at the level of establishments, which are identified by their SIRET. The first nine digits of each SIRET is the firm-level SIREN, which makes it easy to aggregate across establishments for each firm. For each worker, the DADS reports gross and net wages, hours paid, occupation, tenure, gender and age. There is no information about workers' education or overall labor market experience. The data do not include worker identifiers, so we can not track workers over time, but this is of no concern to us given our focus on firm-level rather than individual outcomes.

[^3]
### 4.1.1 Occupations: the PCS

Every job in the DADS is categorized by a two digit PCS occupation code. ${ }^{4}$ Excluding agricultural and public sector categories, the PCS has 22 occupational categories, listed in Table 1. Each two digit PCS category is an aggregate of as many as 40 four digit subcategories, and representative subcategories are shown in Table 2.

Two occupations are central to our research: PCS 38 "Technical managers and engineers" and PCS 47 "Technicians". We refer to workers in these two occupations as "techies". As is clear from the detailed descriptions in Table 2, many workers in these categories are closely connected with the installation, management, maintenance, and support of information and communications technology (ICT), and even if they do not work with ICT these are jobs that require technical training, skill, and experience. Techies mediate the effects of new technology within firms: they are the ones who plan, purchase, and install new ICT equipment, and who train and support other workers in the use of ICT. Inspection of Table 2 supports this argument, though the table also makes it clear that not all of the workers in PCS 38 and 47 necessarily work primarily with ICT. In short, if a firm invests in ICT, it needs techies, and firms with more techies are probably more technologically sophisticated firms.

The techie share of hours as a measure of firm-level technological sophistication can be compared to $\mathrm{R} \& D$ expenditures, a common metric for technology adoption in the literature. Firm-level R\&D is a useful measure, but it excludes much of the ongoing expenditure and managerial attention that firms devote to technology adoption and ICT use. In fact, reported R\&D is surely not even a necessary condition for technology adoption. Conversely, $R \& D$ is likely to be impossible without the employment of techies. Thus, the techie share is a more comprehensive measure of firm-level effort devoted to technology adoption than $\mathrm{R} \& \mathrm{D}$ expenditures.

For the last five years of our sample, 2009-20013, the DADS Poste reports hours by detailed 4 -digit occupation. This allows us to define techies more narrowly starting in 2009, and in what follows, we refer to the aggregate of 2-digit codes 38 and 47 as "broad techies", while "narrow techies" refers to employees who work directly with ICT and/or R\&D.

One potential problem with our hypothesis that firm-level techies are an indicator of firmlevel technological sophistication is that firms can purchase ICT consulting services. By hiring a consultant, firms can obtain and service new ICT without increasing their permanent staff of techies. However, only $0.7 \%$ of broad techie hours are in the IT consulting sector, which implies that more than $99 \%$ of the hourly services supplied by techies are obtained in-house rather than purchased from consultants. ${ }^{5}$

### 4.1.2 Aggregate occupations

Our model includes two labor categories, $S$ and $L$. We measure $L$ as hours worked in PCS codes 53 to 68 (see Table 1 for definitions of these occupations). Though our mnemonic for these workers is "unskilled", the category $L$ includes a wide variety of occupations, some of which are highly skilled, though few if any of the jobs in this category require a university degree. We measure $S$ as hours worked in categories 21 through 48, excluding techies. As with the $L$ aggregate, the "skilled" workers in $S$ work in a wide variety of occupations. Many but not all of these occupations will be dominated by workers with a university education, and most will have at least some post-secondary education.

[^4]The definition of $S$ is narrower when we exclude techies broadly defined (PCS 38 and 47), and broader when we exclude only narrowly defined techies (a subset of the 4 -digit codes that comprise PCS 38 and 47).

### 4.2 Balance sheet data: FICUS and FARE

Firm-level balance sheet information is reported in datasets called FICUS and FARE. ${ }^{6}$ The balance sheet variables used in our empirical analysis include revenue, expenditure on materials, and the book value of capital. We do not use balance sheet data on employment or the wage bill, because the DADS Poste data is more detailed, but the FICUS/FARE wage bill and employment data are extremely highly correlated with the corresponding DADS Poste data.

### 4.2.1 Capital stock

To construct capital stocks, we begin with the book value of capital recorded in FICUS/FARE. We follow the methodology proposed by Cette et al. (Restat, 2015) and Bonleu et al. (2016, Applied Economics). Since the stocks are recorded at historical cost, i.e. at their value at the time of entry into the firm $i$ 's balance sheet, an adjustment, has to be made to move from stocks valued at historic cost $\left(K_{i, s, t}^{B V}\right)$ to stocks valued at current prices ( $K_{i, s, t}$ ). We deflate $K^{B V}$ by a price by assuming that the sectoral price of capital is equal to the sectoral price of investment $T$ years before the date when the first book value was available, where $T$ is the corrected average age of capital, hence $p_{s, t+1}^{K}=p_{s, t-T}^{I}$. The average age of capital is computed using the share of depreciated capital, $D K_{i, s, t}^{B V}$ in the capital stock at historical cost.

$$
T=\frac{D K_{i, s, t}^{B V}}{K_{i, s, t}^{B V}} \times \widetilde{A}
$$

where

$$
\widetilde{A}=\operatorname{median}_{i \in S}\left(\frac{K_{i, s, t}^{B V}}{\Delta D K_{i, s, t}^{B V}}\right)
$$

with S the set of firms in a sector. We use the median value $\widetilde{A}$ to reduce the volatility in the data, as investments within firms happens to be discrete events.

## 5 Estimation and results

In this section we report the results of production function estimation (equation 12), followed by estimation of endogenous productivity (equations 16 and 17).

### 5.1 Estimation

We estimate equation (12) by nonlinear least squares, which is the GMM estimator, separately for 19 industries including both manufacturing and non-manufacturing sectors. Standard errors are clustered by firm. Each industry NLLS regression is an unbalanced panel, which raises the issue of selection bias due to endogenous exit. But as pointed out by Ackerberg et al. (2007), endogenous exit will not bias production function estimation as long as the firm exits in the period after the exit decision has been made. This (often implicit) assumption is now standard in the literature, and we

[^5]make it here. The estimated elasticity of substitution is given by the formula $\widehat{\sigma}=(1-\widehat{\gamma})^{-1}$, with the standard error of $\widehat{\sigma}$ computed by the delta method.

Industry-level production function estimation generates estimated Hicks neutral and skill augmenting productivity for each firm-year. After dropping the highest and lowest percentile of estimated productivity to trim outliers, we estimate the controlled Markov processes given by equations (16) and (17). In these regressions, we measure techies by the lagged share of techies in the firm's wage bill, and we include lagged firm size (measured by lagged revenue) as an additional control. Estimation is by OLS for each industry, with standard errors clustered by firm.

### 5.2 Results: production functions

Our baseline production function estimates are given in Table 3. Each set of two rows is a single industry regression, with standard errors reported below point estimates, and asterisks have the usual interpretation. ${ }^{7}$ The sample period is 2000-2013, and the definition of skilled labor excludes techies broadly defined (PCS 38 and 47). In all industries the point estimate for the elasticity of substitution $\sigma$ is greater than one, and in all but the two smallest industries (coke and refined oil, and pharmaceuticals) we can reject the null hypothesis $\sigma=1$ at the 0.01 significance level. We exclude these two industries from the rest of our analysis. The ability to reject the $\sigma=1$ null is important, because the derivation of our estimating equation requires $\sigma \neq 1$. For all industries, the estimated elasticity of demand $\eta$ is statistically significantly less than -1 , as required by theory. The distribution parameters $\alpha_{L}, \alpha_{S}, \alpha_{K}$ and $\alpha_{M}$ are all estimated precisely and are statistically significantly greater than zero.

The estimates reported in Table 4 use a definition of $S$ that excludes only narrowly defined techies, and as a consequence measured $S$ is weakly larger than it was in the baseline specification reported in Table 3. Not surprisingly, the estimates for $\alpha_{S}$ are somewhat higher in Table 4 than they were in Table 3. Because data on narrowly defined techies is only available starting in 2009, the sample in Table 4 is shorter, and standard errors are somewhat larger than in Table 3. However, the point estimates are broadly similar across the two tables.

Our last set of production function estimates combines the broad definition of techies with the shorter 2009-2013 period, and is reported in Table 5. The results from Table 5 are broadly consistent with the results reported in Tables 3 and 4.

### 5.3 Results: endogenous productivity

Our main objective in estimating production functions is to recover estimated productivity, so the production function estimates just discussed are of limited interest by themselves. We now turn to our primary research objective, which is to understand the dynamics of firm-level productivity and the associated implications for labor demand. Our tool for this is estimation of equations (16) and (17).

Table 6 reports our baseline estimates, using the estimated productivity series from the production function estimates reported in Table 3. The first four columns report, for each industry, the results of regressing Hicks neutral productivity $\omega_{H f t}$ on the lagged share of techies in the firm's wage bill, lagged Hicks neutral and skill augmenting productivity, lagged firm size, and year fixed effects. The final four columns regress skill augmenting productivity $\omega_{S f t}$ on the same regressors. The first row reports results from pooled regressions across all industries, with industry $\times$ year fixed effects. While these pooled regressions have no structural interpretation, they are nonetheless

[^6]a useful summary of the industry regressions in the rows below: the effect of lagged techies on Hicks neutral productivity is tiny and statistically insignificant, while the effect on skill augmenting productivity is large and precisely estimated, with a coefficient of 0.48 . These estimates imply that a firm with a 10 percentage point higher techie share will have skill augmenting productivity that is 5 percentage points higher, but no difference in Hicks neutral productivity. The pooled techie effects are reflective of the industry-by-industry results. As can be seen in column 5, the lagged techie effect on $\omega_{\text {Sft }}$ is statistically significant in every industry and large in most, with estimates ranging from 0.18 to 1.5 . By contrast, the effects of lagged techies on $\omega_{H f t}$ reported in column 1 are more mixed:

- 7 are statistically significant and positive, though in each case no larger than the corresponding effects on $\omega_{S f t}$.
- 5 are statistically insignificant.
- 5 statistically significant and negative, though in each case smaller in absolute value than the corresponding effects on $\omega_{S f t}$.
The largest negative techie effects on $\omega_{H f t}$ are in industries (computers and equipment) where our assumption that broad techies (which includes engineers and technical managers as well as ICT and R\&D workers) do not affect current output is less credible.

A novel feature of our project is that we estimate productivity for six non-manufacturing sectors, the final six reported in each table. These sectors account for the bulk of output and employment in our sample, and the techie effects on productivity are instructive: techies raise $\omega_{S f t}$ modestly (except for Accommodation and Food, where the effect is very large), while techies have a modest positive effect on $\omega_{H f t}$ in three sectors and a near-zero effect in the other three.

Table 7 reports estimates using the narrow definition of techies on the 2009-2013 sample. The estimated effects are broadly similar to those found in Table 6, though the point estimates are smaller, and there are fewer statistically significant techie effects (positive or negative) on $\omega_{H f t}$. In every sector except one (Accommodation and Food), the effect of techies on $\omega_{S f t}$ is statistically significant, positive, and in most cases large, with a pooled estimated effect of 0.55 that is essentially the same as found in Table 6. The results reported in Table 8, which uses broad techies on the shorter sample, are broadly consistent with Tables 6 and 7 .

Table 9 summarizes our findings on the effects of techies on productivity. The estimated techie coefficients reported in Tables 6,7 and 8 are multiplied by the median level of the techie share for firms with positive techies, so that the effects reported in Table 9 answer the following question: how does productivity differ for firms with the median level of techies compared to firms with no techies? The total effect of techies on firm performance includes the effect on both $\omega_{H f t}$ and on $\omega_{S f t}$, and for the median firm in the sample this total effect is given by $\omega_{H f t}+\alpha_{S} \omega_{S f t}$, also multiplied by the median techie share. The pooled overall effects are positive though small: in the baseline the effect is about 1 percentage point, and for the shorter samples the pooled effect is 0.2 to 0.3 percentage points. ${ }^{8}$

## 6 Conclusion

This document reports work in progress, but we have made enough progress to come to some provisional conclusions. The production functions estimated in section 5.2 were characterized by

[^7]elasticities of substitution that are greater than one, often substantially so. The endogenous productivity estimates of section 5.3 show that techies have a large, positive effect on skill augmenting productivity. These two findings imply that techies cause firm-level skill upgrading. We conclude that in our dataset firm-level technological progress is strongly skill biased: technology adoption mediated by techies causes skill upgrading.

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Table 1: PCS Occupations

| PCS code | description of occupation | rank | share |
| :--- | :--- | ---: | ---: |
| 21 | Small business owners and workers | 7 | 0.1 |
| 22 | Shopkeepers | 3 | 0.2 |
| 23 | Heads of businesses | 1 | 0.7 |
| 34 | Scientific and educational professionals | 5 | 0.5 |
| 35 | Creative professionals | 6 | 0.6 |
| $\mathbf{3 7}$ | Top managers and professionals | $\mathbf{2}$ | $\mathbf{7 . 3}$ |
| $\mathbf{3 8}$ | Technical managers and engineers | $\mathbf{4}$ | $\mathbf{6 . 2}$ |
| 42 | Teachers | 9 | 0.3 |
| 43 | Mid-level health professionals | 12 | 1.2 |
| $\mathbf{4 6}$ | Mid-level managers \& professionals | $\mathbf{1 1}$ | $\mathbf{1 2 . 2}$ |
| $\mathbf{4 7}$ | Technicians | $\mathbf{1 0}$ | $\mathbf{5 . 0}$ |
| $\mathbf{4 8}$ | Supervisors and foremen | $\mathbf{8}$ | $\mathbf{2 . 9}$ |
| 53 | Security workers | 18 | 1.0 |
| $\mathbf{5 4}$ | Office workers | $\mathbf{1 6}$ | $\mathbf{1 1 . 6}$ |
| $\mathbf{5 5}$ | Retail workers | $\mathbf{2 0}$ | $\mathbf{7 . 0}$ |
| $\mathbf{5 6}$ | Personal service workers | $\mathbf{2 1}$ | $\mathbf{4 . 1}$ |
| $\mathbf{6 2}$ | Skilled industrial workers | $\mathbf{1 3}$ | $\mathbf{1 1 . 0}$ |
| $\mathbf{6 3}$ | Skilled manual laborers | $\mathbf{1 7}$ | $\mathbf{8 . 5}$ |
| $\mathbf{6 4}$ | Drivers | $\mathbf{1 4}$ | $\mathbf{5 . 1}$ |
| $\mathbf{6 5}$ | Skilled transport and wholesale workers | $\mathbf{1 5}$ | $\mathbf{2 . 7}$ |
| $\mathbf{6 7}$ | Unskilled industrial workers | $\mathbf{1 9}$ | $\mathbf{8 . 2}$ |
| $\mathbf{6 8}$ | Unskilled manual laborers | $\mathbf{2 2}$ | $\mathbf{3 . 7}$ |

Note to Table 1: "rank" is the occupation's wage rank in 2002, "share" is occupation's share of hours paid in 2002. Occupations in bold are account for at least 2.5 percent of hours.
Table 2: PCS 2-digit occupations and representative 4-digit suboccupations

| 37 | Top managers and professionals | 56 | Personal service workers |
| :---: | :---: | :---: | :---: |
|  | Managers of large businesses |  | Restaurant servers, food prep workers |
|  | Finance, accounting, sales, and advertising managers |  | Hotel employees: front desk, cleaning, other |
|  | Other administrative managers |  | Barbers, hair stylists, and beauty shop employees |
| 38 | Technical managers and engineers (techies) |  | Child care providers, home health aids |
|  | Technical managers for large companies |  | Residential building janitors, caretakers |
|  | Engineers and R\&D managers | 62 | Skilled industrial workers |
|  | Eletrical, mechanical, materials and chemical engineers |  | Skilled construction workers |
|  | Purchasing, planning, quality control, and production managers |  | Skilled metalworkers, pipefitters, welders |
|  | Information technology R\&D engineers and managers |  | Skilled heavy and electrical machinery operators |
|  | Information technology support engineers and managers |  | Skilled operators of electrical and electronic equipment |
|  | Telecommunications engineers and specialists |  | Skilled workers in various industries |
| 46 | Mid-level professionals | 63 | Skilled manual laborers |
|  | Mid-level professionals, various industries |  | Gardeners |
|  | Supervisors in financial, legal, and other services |  | Master electricians, bricklayers, carpenters, etc |
|  | Store, hotel, and food service managers |  | Skilled electrical and electronice service technicians |
|  | Sales and PR representatives |  | Skilled autobody and autorepair workers |
| 47 | Technicians (techies) |  | Master cooks, bakers, butchers |
|  | Designers of electrical, electronic, and mechanical equipment |  | Skilled artisans (jewelers, potters, etc) |
|  | R\&D technicians, general and IT | 64 | Drivers |
|  | Installation and maintenance of non-IT equipment |  | Truck, taxi, and delivery drivers |
|  | Installation and maintenance of IT equipment | 65 | Skilled transport workers |
|  | Telecommunications and computer network technicians |  | Heavy crane and vehicle operators |
|  | Computer operation, installation and maintenance technicians |  | Warehouse truck and forklift drivers |
| 48 | Foremen, Supervisors |  | Other skilled warehouse workers |
|  | Foremen: construction and other | 67 | Low skill industrial workers |
|  | Supervisors: various manufacturing sectors |  | Low skill construction workers |
|  | Supervisors: maintenance and installation of machinery |  | low skill electrical, metalworking, and mechanical workers |
|  | Warehouse and shipping managers |  | low skill shipping, moving, and warehouse workers |
|  | Food service supervisors |  | Other low skill transport industry workers |
| 54 | Office workers |  | Low skill production workers in various industries |
|  | Receptionists, secretaries | 68 | Low skill manual laborers |
|  | Administrative/clerical workers, various sectors |  | Low skill mechanics, locksmiths, etc |
|  | Computer operators |  | Apprentice bakers, butchers |
|  | Bus/train conductors, etc |  | Building cleaners, street cleaners, sanitation workers |
| 55 | Retail workers |  | Various low skill manual laborers |
|  | Retail employees, various establishments |  |  |
|  | Cashiers |  |  |
|  | Service station attendants |  |  |

Table 5: Production function estimates, broad techies, 2009-2013




Table 6: Endogenous productivity estimates, broad techies, 2000-2013

| techies $_{\text {ft-1 }}$ | $\omega_{f t-1}^{H}$ | $\omega_{f t-1}^{S}$ | $\log$ size $_{\text {ft-1 }}$ | techies $_{\text {ft-1 }}$ | $\omega_{f t-1}^{H}$ | $\omega_{f t-1}^{S}$ | $\log \operatorname{size}_{f t-1}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| -0.001 | 0.779*** | $0.056^{* * *}$ | -0.027*** | $0.479^{* * *}$ | $0.032^{* * *}$ | $0.712^{* * *}$ | $-0.007^{* * *}$ |
| 0.007 | 0.002 | 0.001 | 0.001 | 0.008 | 0.001 | 0.002 | 0.001 |
| $-0.260^{* * *}$ | 0.819*** | 0.023*** | $-0.103^{* * *}$ | 0.799*** | 0.021*** | $0.741^{* * *}$ | 0.018*** |
| 0.044 | 0.008 | 0.002 | 0.005 | 0.056 | 0.005 | 0.005 | 0.004 |
| 0.031 | $0.795^{* * *}$ | 0.020*** | -0.071*** | 0.591*** | -0.007 | $0.746^{* * *}$ | $0.020^{* *}$ |
| 0.055 | 0.007 | 0.005 | 0.004 | 0.056 | 0.005 | 0.007 | 0.004 |
| $0.375^{* * *}$ | $0.763^{* * *}$ | 0.052*** | $-0.042^{* * *}$ | $1.520^{* * *}$ | 0.091*** | 0.710*** | -0.089*** |
| 0.055 | 0.008 | 0.003 | 0.004 | 0.089 | 0.007 | 0.005 | 0.007 |
| 0.053 | 0.769*** | $0.037^{* * *}$ | $-0.084^{* * *}$ | $0.418^{* *}$ | $0.061 * * *$ | 0.804*** | 0.008 |
| 0.058 | 0.013 | 0.007 | 0.007 | 0.061 | 0.009 | 0.009 | 0.006 |
| 0.204*** | $0.834^{* * *}$ | 0.035*** | -0.072*** | $1.073^{* * *}$ | $0.037 * * *$ | 0.729*** | -0.025*** |
| 0.051 | 0.008 | 0.003 | 0.005 | 0.079 | 0.007 | 0.006 | 0.007 |
| $0.252^{* * *}$ | $0.812^{* * *}$ | $0.037^{* * *}$ | $-0.057^{* * *}$ | 0.570*** | 0.009** | 0.705*** | $-0.048^{* * *}$ |
| 0.023 | 0.006 | 0.002 | 0.003 | 0.034 | 0.004 | 0.005 | 0.004 |
| $-0.333^{* * *}$ | $0.675^{* * *}$ | 0.050*** | $-0.082^{* * *}$ | $0.458^{* * *}$ | $0.073^{* * *}$ | $0.725^{* * *}$ | -0.006 |
| 0.044 | 0.014 | 0.009 | 0.007 | 0.033 | 0.008 | 0.011 | 0.005 |
| $-0.213^{* *}$ | $0.725^{* * *}$ | 0.039*** | $-0.074^{* * *}$ | $0.701^{* * *}$ | $0.065^{* * *}$ | 0.749*** | -0.015* |
| 0.085 | 0.021 | 0.008 | 0.008 | 0.083 | 0.015 | 0.015 | 0.009 |
| $-0.315^{* * *}$ | $0.696^{* * *}$ | 0.019*** | -0.060*** | $1.088^{* * *}$ | 0.070*** | 0.730*** | $-0.024^{* * *}$ |
| 0.063 | 0.014 | 0.005 | 0.007 | 0.068 | 0.010 | 0.008 | 0.008 |
| -0.057 | $0.784^{* * *}$ | 0.020*** | -0.099*** | $0.504^{* * *}$ | $0.066^{* * *}$ | 0.749*** | 0.013 |
| 0.064 | 0.013 | 0.005 | 0.008 | 0.082 | 0.011 | 0.011 | 0.009 |
| 0.051*** | $0.752^{* * *}$ | $0.086^{* * *}$ | -0.085*** | $0.182^{* * *}$ | $0.026^{* * *}$ | 0.683*** | -0.002 |
| 0.014 | 0.006 | 0.004 | 0.003 | 0.011 | 0.003 | 0.005 | 0.002 |
| $-0.071^{* * *}$ | $0.710^{* * *}$ | 0.055*** | $-0.066^{* * *}$ | 0.429*** | $0.046^{* * *}$ | $0.697^{* * *}$ | -0.009*** |
| 0.011 | 0.005 | 0.002 | 0.002 | 0.010 | 0.002 | 0.002 | 0.001 |
| 0.219*** | $0.736^{* * *}$ | 0.068*** | 0.059*** | $0.312^{* * *}$ | $0.027^{* * *}$ | 0.772*** | -0.001** |
| 0.018 | 0.003 | 0.002 | 0.001 | 0.009 | 0.001 | 0.002 | 0.001 |
| $0.173^{* * *}$ | 0.848*** | 0.051*** | -0.065*** | $0.173^{* * *}$ | $0.015^{* * *}$ | 0.712*** | $-0.006^{* * *}$ |
| 0.026 | 0.005 | 0.004 | 0.003 | 0.018 | 0.002 | 0.005 | 0.001 |
| 0.187** | $0.721^{* * *}$ | 0.032*** | $-0.029^{* * *}$ | $1.560^{* * *}$ | $0.068^{* * *}$ | $0.661^{* * *}$ | $-0.021^{* * *}$ |
| 0.093 | 0.006 | 0.001 | 0.001 | 0.178 | 0.005 | 0.003 | 0.003 |
| -0.045 | $0.648^{* * *}$ | 0.040*** | 0.015 | $0.258^{* * *}$ | 0.100*** | $0.788^{* * *}$ | 0.025*** |
| 0.060 | 0.014 | 0.012 | 0.009 | 0.044 | 0.008 | 0.009 | 0.006 |
| -0.028 | 0.809*** | 0.061*** | $-0.062^{* * *}$ | $0.461{ }^{* * *}$ | $0.036^{* * *}$ | 0.711*** | 0.001 |
| 0.024 | 0.006 | 0.003 | 0.002 | 0.026 | 0.004 | 0.006 | 0.002 |

All industries
Food, beverage, tobacco
Textiles, apparel
Wood, paper products
Chemical products
Rubber \& plastic
Basic \& fabricated metal
Computer, electronic
Electrical equipment
Machinery \& equipment
Transport equipment
Other manufacturing
Construction
Wholesale \& retail
Transport \& storage
Accommodation and food
Publishing \& broadcast
Admin \& support
Table 7: Endogenous productivity estimates, narrow techies, 2009-2013
 $\qquad$
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$0.803^{* * *}$
0.015
$0.842^{* * *}$
0.013
$0.856^{* * *}$
0.010 $0.008^{* *}$ $0.819^{* * *}$
0.014 $0.722^{* * *}$ ${ }^{0.006}$ **** . 003 $0.791 * *$
0.002 ${ }_{0.776 * * *}$ 0.006 0.737*** 004 $0.004{ }^{* * *}$ . 012 $\stackrel{*}{*_{2}^{*}}$ 0.006 $0.554^{* * *}$ ${ }^{0.028}{ }^{1.008^{* *}}$ $1.008^{* * *}$
0.192
$1.151 * * *$ $1.151^{* * *}$ 3.373*** 0.486 0.491 *** $0.14{ }^{*} * * *$ 1.856
0.321 $0.535^{* * *}$ 0.072 $0.538^{* * *}$

0.086 $0.767^{* * *}$ $0.056^{* * *}$ 0.012 $\stackrel{*}{*}$ 0 082\%** 0.004 $-0.054^{* * *}$ | $0.0 .003^{* * *}$ |
| :--- |
| $-0.03)^{2}$ |

 0.009 $\underbrace{-0.057^{2 * * * *}}_{0} 0$
 0.010禀 $0.992^{* * *}$
0.199 0.10*** 0.037*** $0.012^{* * *}$ $0.011^{* * *}$
0.004 ${ }_{0}^{0.0021 * * *}$
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Textiles, apparel

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Chemical products
Rubber \& plastic
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Computer, electronic
Electrical equipment

Transport equipment
Other manufacturing
Publishing \& broadcast

$$
\begin{aligned}
& -0.039^{* * *} \\
& 0.001
\end{aligned}
$$

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Table 8: Endogenous productivity estimates, broad techies, 2009-2013

| Hicks neutral productivity $\omega_{f t}^{H}$ |  |  |  | skill augmenting productivity $\omega_{f t}^{S}$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| techies $_{\text {ft-1 }}$ | $\omega_{f t-1}^{H}$ | $\omega_{f t-1}^{S}$ | $\log$ size $_{\text {ft-1 }}$ | techies $_{\text {ft-1 }}$ | $\omega_{f t-1}^{H}$ | $\omega_{f t-1}^{S}$ | $\log \operatorname{size}_{f t-1}$ |
| -0.027** | $0.774^{* * *}$ | 0.044*** | -0.050*** | 0.274*** | $0.028^{* * *}$ | 0.735*** | -0.007*** |
| 0.011 | 0.003 | 0.002 | 0.001 | 0.011 | 0.002 | 0.003 | 0.001 |
| $-0.344^{* * *}$ | $0.796^{* * *}$ | 0.018*** | $-0.126^{* * *}$ | 0.509*** | 0.006 | 0.724*** | 0.001 |
| 0.082 | 0.019 | 0.004 | 0.011 | 0.081 | 0.011 | 0.009 | 0.007 |
| -0.081 | $0.771^{* * *}$ | -0.009 | $-0.061^{* * *}$ | $0.570^{* * *}$ | $-0.020^{* *}$ | 0.760 *** | 0.010 |
| 0.123 | 0.015 | 0.009 | 0.008 | 0.119 | 0.010 | 0.011 | 0.008 |
| 0.314*** | $0.747^{* * *}$ | 0.026*** | $-0.066^{* * *}$ | $1.069^{* * *}$ | $0.073^{* * *}$ | 0.768*** | $-0.106^{* * *}$ |
| 0.118 | 0.020 | 0.006 | 0.009 | 0.153 | 0.013 | 0.009 | 0.013 |
| 0.222* | 0.754*** | 0.064*** | $-0.106^{* * *}$ | 0.192* | 0.082*** | 0.823*** | 0.032*** |
| 0.116 | 0.028 | 0.016 | 0.015 | 0.108 | 0.017 | 0.014 | 0.011 |
| 0.043 | $0.807^{* * *}$ | 0.025*** | -0.085*** | 0.759*** | $0.035^{* * *}$ | 0.758*** | -0.026** |
| 0.113 | 0.018 | 0.006 | 0.010 | 0.143 | 0.012 | 0.010 | 0.011 |
| 0.112*** | 0.794*** | 0.028*** | $-0.081^{* * *}$ | 0.292*** | -0.001 | $0.720^{* * *}$ | -0.039*** |
| 0.036 | 0.013 | 0.004 | 0.005 | 0.043 | 0.007 | 0.010 | 0.005 |
| $-0.627^{* * *}$ | 0.622*** | 0.072*** | -0.089*** | $0.516^{* * *}$ | 0.093*** | 0.708*** | -0.007 |
| 0.100 | 0.031 | 0.022 | 0.014 | 0.063 | 0.015 | 0.022 | 0.009 |
| $-0.411^{* * *}$ | $0.646^{* * *}$ | 0.017 | $-0.103^{* * *}$ | 0.469*** | $0.073^{* * *}$ | $0.753^{* * *}$ | -0.003 |
| 0.154 | 0.041 | 0.015 | 0.016 | 0.132 | 0.028 | 0.021 | 0.014 |
| $-0.697^{* * *}$ | 0.634*** | -0.002 | -0.050*** | 0.842*** | $0.065^{* * *}$ | $0.758^{* * *}$ | -0.028*** |
| 0.099 | 0.023 | 0.009 | 0.010 | 0.089 | 0.014 | 0.015 | 0.010 |
| -0.157* | $0.756^{* * *}$ | 0.017 | $-0.101^{* * *}$ | $0.357^{* * *}$ | $0.051^{* * *}$ | $0.768^{* * *}$ | 0.008 |
| 0.093 | 0.027 | 0.010 | 0.015 | 0.101 | 0.015 | 0.017 | 0.011 |
| 0.020 | 0.760*** | 0.082*** | -0.098*** | $0.122^{* * *}$ | 0.006 | $0.645^{* * *}$ | -0.010*** |
| 0.023 | 0.008 | 0.007 | 0.004 | 0.017 | 0.005 | 0.010 | 0.003 |
| $-0.084^{* * *}$ | 0.718*** | 0.061*** | -0.095*** | 0.206*** | $0.024^{* *}$ | $0.647^{* * *}$ | -0.010*** |
| 0.014 | 0.007 | 0.003 | 0.003 | 0.011 | 0.003 | 0.005 | 0.002 |
| 0.306*** | 0.769*** | 0.143*** | $-0.008^{* * *}$ | $0.103^{* * *}$ | $0.016^{* * *}$ | $0.727^{* * *}$ | 0.005*** |
| 0.024 | 0.005 | 0.005 | 0.001 | 0.010 | 0.001 | 0.005 | 0.001 |
| 0.219*** | 0.870*** | 0.048*** | -0.044*** | 0.177*** | 0.021*** | 0.733*** | -0.008*** |
| 0.045 | 0.006 | 0.006 | 0.003 | 0.030 | 0.004 | 0.008 | 0.002 |
| 0.288 | 0.734*** | 0.025*** | $-0.034^{* * *}$ | 0.784** | 0.031*** | 0.690*** | -0.046*** |
| 0.248 | 0.012 | 0.002 | 0.002 | 0.328 | 0.007 | 0.005 | 0.004 |
| -0.125 | 0.708*** | 0.070*** | -0.009 | 0.298*** | $0.078^{* * *}$ | 0.770*** | 0.045*** |
| 0.079 | 0.018 | 0.013 | 0.010 | 0.068 | 0.013 | 0.016 | 0.008 |
| -0.076** | 0.843*** | 0.051*** | -0.044*** | 0.449*** | 0.009 | 0.730*** | -0.016*** |
| 0.038 | 0.009 | 0.005 | 0.004 | 0.042 | 0.007 | 0.010 | 0.004 |

All industries
Food, beverage, tobacco
Textiles, apparel
Wood, paper products
Chemical products
Rubber \& plastic
Basic \& fabricated metal
Computer, electronic
Electrical equipment
Machinery \& equipment
Transport equipment
Other manufacturing
Construction
Transport \& storage
Accommodation and food
Publishing \& broadcast
Chin \& support
Cetail
Table 9: Scaled effects of techies on productivity

| Broad techies, 2000-2013 |  |  | Narrow techies, 2009-2013 |  |  | Broad techies, 2009-2013 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\omega^{H}$ | $\omega^{S}$ | $\omega^{H}+a_{S} \omega^{S}$ | $\omega^{H}$ | $\omega^{S}$ | $\omega^{H}+a_{S} \omega^{S}$ | $\omega^{H}$ | $\omega^{S}$ | $\omega^{H}+a_{S} \omega^{S}$ |
| -0.0002 | 0.0671*** | 0.0087 | -0.0041*** | $0.0313^{* * *}$ | 0.0018 | -0.0038** | 0.0384*** | 0.0030 |
| 0.0010 | 0.0011 |  | 0.0015 | 0.0016 |  | 0.0016 | 0.0015 |  |
| $-0.0263^{* * *}$ | 0.0806*** | $-0.0217^{* * *}$ | 0.0046 | 0.0317*** | 0.0064 | -0.0403*** | 0.0595*** | $-0.0373^{* * *}$ |
| 0.0044 | 0.0057 | 0.0044 | 0.0042 | 0.0061 | 0.0042 | 0.0096 | 0.0094 | 0.0096 |
| 0.0030 | 0.0585 *** | 0.0119** | -0.0072 | 0.0389*** | -0.0003 | -0.0105 | $0.0740^{* * *}$ | 0.0002 |
| 0.0054 | 0.0056 | 0.0055 | 0.0117 | 0.0106 | 0.0119 | 0.0159 | 0.0154 | 0.0161 |
| 0.0443*** | 0.1795*** | $0.0667^{* * *}$ | 0.0067 | 0.1235*** | 0.0254** | $0.0464^{* * *}$ | 0.1583*** | $0.0643^{* * *}$ |
| 0.0065 | 0.0105 | 0.0067 | 0.0099 | 0.0178 | 0.0103 | 0.0175 | 0.0226 | 0.0177 |
| 0.0115 | 0.0903*** | 0.0215* | 0.0128 | 0.0394*** | 0.0184* | 0.0509* | 0.0439* | 0.0552** |
| 0.0125 | 0.0133 | 0.0126 | 0.0103 | 0.0116 | 0.0105 | 0.0265 | 0.0246 | 0.0266 |
| 0.0295*** | $0.1556^{* * *}$ | 0.0405*** | -0.0093 | 0.0929*** | -0.0003 | 0.0072 | 0.1250*** | 0.0157 |
| 0.0074 | 0.0115 | 0.0074 | 0.0095 | 0.0160 | 0.0097 | 0.0186 | 0.0236 | 0.0187 |
| 0.0404*** | 0.0913*** | 0.0502*** | 0.0045 | 0.0357** | 0.0100** | $0.0213^{* * *}$ | 0.0554*** | 0.0266** |
| 0.0037 | 0.0054 | 0.0037 | 0.0036 | 0.0048 | 0.0037 | 0.0069 | 0.0082 | 0.0069 |
| $-0.1180^{* * *}$ | 0.1622*** | -0.0910*** | -0.0726*** | 0.0929*** | -0.0479** | -0.2662*** | 0.2192*** | $-0.2348^{* * *}$ |
| 0.0154 | 0.0119 | 0.0156 | 0.0197 | 0.0149 | 0.0201 | 0.0425 | 0.0267 | 0.0427 |
| -0.0520** | 0.1710*** | -0.0348* | -0.0234 | 0.0763*** | -0.0108 | -0.1243*** | 0.1417*** | -0.1112** |
| 0.0206 | 0.0203 | 0.0207 | 0.0190 | 0.0165 | 0.0192 | 0.0466 | 0.0399 | 0.0468 |
| $-0.0818^{* * *}$ | $0.2826^{* * *}$ | -0.0535*** | -0.0522*** | 0.1037*** | -0.0327* | -0.2225*** | 0.2689*** | -0.1978*** |
| 0.0162 | 0.0176 | 0.0163 | 0.0168 | 0.0155 | 0.0171 | 0.0316 | 0.0284 | 0.0317 |
| -0.0110 | 0.0981** | -0.0059 | 0.0037 | 0.0691** | 0.0105 | -0.0364* | 0.0830** | -0.0322 |
| 0.0124 | 0.0160 | 0.0125 | 0.0119 | 0.0138 | 0.0120 | 0.0216 | 0.0234 | 0.0217 |
| 0.0085*** | 0.0304*** | $0.0142^{* * *}$ | -0.0083*** | 0.0131*** | -0.0050 | 0.0039 | $0.0244^{* * *}$ | 0.0088* |
| 0.0024 | 0.0018 | 0.0024 | 0.0032 | 0.0022 | 0.0032 | 0.0046 | 0.0035 | 0.0047 |
| $-0.0086^{* * *}$ | 0.0517*** | -0.0028** | -0.0043* | 0.0076*** | -0.0032 | $-0.0127^{* * *}$ | 0.0314*** | -0.0093 *** |
| 0.0014 | 0.0012 | 0.0014 | 0.0025 | 0.0017 | 0.0025 | 0.0021 | 0.0017 | 0.0021 |
| 0.0145*** | 0.0206*** | $0.0194^{* * *}$ | 0.0079*** | 0.0041** | 0.0091** | $0.0343^{* * *}$ | $0.0116^{* * *}$ | 0.0375*** |
| 0.0012 | 0.0006 | 0.0012 | 0.0022 | 0.0010 | 0.0023 | 0.0027 | 0.0011 | 0.0027 |
| 0.0085*** | 0.0084*** | 0.0095*** | -0.0006 | 0.0045** | 0.0000 | $0.0137^{* * *}$ | 0.0111*** | 0.0150*** |
| 0.0013 | 0.0009 | 0.0013 | 0.0023 | 0.0022 | 0.0023 | 0.0028 | 0.0019 | 0.0029 |
| 0.0007** | 0.0062*** | $0.0014^{* * *}$ | -0.0002 | 0.0088 | 0.0007 | 0.0065 | 0.0177** | 0.0084 |
| 0.0004 | 0.0007 | 0.0004 | 0.0018 | 0.0059 | 0.0019 | 0.0056 | 0.0074 | 0.0057 |
| -0.0045 | $0.0256^{* * *}$ | 0.0100 | -0.0076 | 0.0300*** | 0.0095 | -0.0186 | $0.0443^{* * *}$ | 0.0056 |
| 0.0059 | 0.0044 | 0.0064 | 0.0098 | 0.0082 | 0.0108 | 0.0117 | 0.0102 | 0.0130 |
| -0.0017 | 0.0287*** | 0.0031** | -0.0032 | 0.0264*** | 0.0015 | -0.0075** | $0.0441^{* * *}$ | -0.0005 |
| 0.0015 | 0.0016 | 0.0015 | 0.0028 | 0.0028 | 0.0028 | 0.0037 | 0.0042 | 0.0038 |

All industries
Food, beverage, tobacco
Textiles, apparel
Wood, paper products
Chemical products
Rubber \& plastic
Basic \& fabricated metal
Computer, electronic
Electrical equipment
Machinery \& equipment
Transport equipment
Other manufacturing
Construction
Wholesale \& retail
Transport \& storage
Accommodation and food
Publishing \& broadcast
Admin \& support


[^0]:    *This document reports preliminary results from work in progress, and was prepared solely for discussion at the June 2017 conference "Globalization and New Technology: Effects on Firms and Workers" in Stockholm. Please do not circulate or cite.
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[^1]:    ${ }^{1}$ To understand the relevance and importance of normalizing the CES production function, see the discussion and references on page 668 of Grieco et al. (2016)

[^2]:    ${ }^{2}$ that is, before the revenue shock $u_{f t}$ is realized.

[^3]:    ${ }^{3}$ The DADS Poste is an INSEE database compiled from the mandatory firm-level DADS ("Déclaration Annuelle de Données Sociales") reports.

[^4]:    ${ }^{4}$ PCS stands for"Professions et Catégories Socioprofessionnelles".
    ${ }^{5}$ We refer to the IT consulting sector as industry code 72 in the NAF classification, which includes the following subcategories: Hardware consultancy, Publishing of software, Other software consultancy and supply, Data processing, Database activities, Maintenance and repair of office, Accounting and computing machinery, and Other computer related activities

[^5]:    ${ }^{6}$ FICUS (Fichier complet unifié de SUSE) reports balance sheet data through 2007, while FARE (Fichier approché des résultats Ésane) starts in 2008. The underlying data sources are identical.

[^6]:    ${ }^{7 *}=$ statistically significantly different from zero at the $10 \%$ confidence level, ${ }^{* *}=5 \%$ confidence, and ${ }^{* * *}=1 \%$ confidence.

[^7]:    ${ }^{8}$ To compute the pooled overall effects requires a pooled estimate of $\alpha_{S}$, which is not estimated. We use a revenueweighted average of the industry $\alpha_{S}$ 's, but since there is no standard error on this ad hoc approximation the standard errors on the overall pooled effects are not defined.

